Temperature and decisions: evidence from 207,000 court cases

Article (Accepted Version)

Heyes, Anthony and Saberian, Soodeh (2019) Temperature and decisions: evidence from 207,000 court cases. American Economic Journal: Applied Economics, 11 (2). pp. 238-65. ISSN 1945-7782

Temperature and Decisions: Evidence from 207,000 Court Cases*

Anthony Heyes
University of Ottawa
University of Sussex

Soodeh Saberian
University of Ottawa

April 25, 2018

Abstract

We analyze the impact of outdoor temperature on high-stakes decisions (immigration adjudications) made by professional decision-makers (US immigration judges). In our preferred specification, which includes spatial, temporal and judge fixed effects, and controls for various potential confounders, a 10 °F degree increase in case-day temperature reduces decisions favorable to the applicant by 6.55%. This is despite judgements being made indoors, 'protected' by climate-control. Results are consistent with established links from temperature to mood and risk appetite and have important implications for evaluating the influence of climate on 'cognitive output'.

Keywords: Decision-making - temperature - adaptation - biology and economics.

*Anthony Heyes is Canada Research Chair (CRC) in Environmental Economics at University of Ottawa and part-time Professor of Economics at the University of Sussex. He acknowledges financial support from the CRC Program and from SSHRC under Insight Grant # 435-2012-472. We are grateful to Alberto Salvo, Alexandre Mas, Ben Olken, Maya Papineau, Matthew Neidell, John List, Patrick Baylis, Pierre Brochu, Sandeep Kapur, Jason Garred, Abel Brodeur, two referees from this journal and seminar participants at CREE 2017 at Ivey Business School at Western University, University of Exeter, University of Sussex, National University of Singapore and McGill University for helpful conversations. Errors are ours.

1 Introduction

We investigate the link from outdoor temperature to decisions made by experienced professional decision-makers, working in good quality, climate controlled indoor spaces. If decisions with durable consequences are systematically influenced by irrelevant factors the potential for welfare loss is obvious. The question we investigate is the following: do decision outcomes, the substance of which have nothing to do with contemporaneous temperature, depend causally on how hot it is outside on the day the decision is made? Examining the universe of files (just under 207 000) evaluated over a four year period by the 266 immigration court judges at the 43 US Federal Immigration Courthouse locations spread across most major US cities our answer is a resounding yes - with high significance and robustness, and a substantial effect size. As such we evidence a subtle and pernicious channel through which variations in climate (across space and through time) can damage wellbeing: By influencing decisions.

The analysis contributes to our developing understanding of how decisions can be sensitive to apparently irrelevant considerations. For examples, Mani et al. (2013) show that poverty, by occupying scarce mental resources or 'bandwidth', reduces cognitive function and reduces decision quality. Hunger negatively influences mental function (Weaver and Hadley (2009) and Weinreb et al. (2002)) and perception of risk (Ferrarelli (2016)). Tiredness reduces cognitive function (Tchen et al. (2003), Abd-Elfattah et al. (2015)), increases risk-taking (Viner et al. (2008)) and reduces self-control (Kahol et al. (2008)).[1] A wider set of behavioral research, consistent with introspection, points to the importance of transitory emotions and mind-states in influencing decisions with long-term consequences (see Loewenstein (1996) for an early survey). For instance, while Ariely and Loewenstein (2006) show that sexual arousal can impact sexual decision-making, Jahedi et al. (2016) show that it can also influence a wider set of economic decisions by temporarily distorting risk attitudes. The results extend recent research that shows the effect of weather on student test performance (for example Park (2016)) to high-stakes, workplace 'cognitive output'. All of these fit into the 'biology and economics' agenda that seeks to model the agents that populate economic textbooks as biological organisms ('wet machines') - sensitive to the environment in which they function.

Four things make the immigration court system setting an ideal test-bed for the theories that we investigate;

(1) The decisions that we observe are socially and economically important and the appropriate choice self-evidently has nothing to do with contemporaneous temperature.

[1]There is a philosophical debate about how to conduct welfare analysis in these settings (Diamond and Vartiainen (2012)). Typically preferences (say with respect to risk) are regarded as having some longevity. If a person who has lost a night of sleep due to construction noise acts "as if" they have a higher risk appetite than they otherwise would then emerging practice would be to treat the misdecisions made as welfare-reducing (O'Brien and Mindell (2005) and Halleröd and Larsson (2008)).

As such any influence of temperature on decisions necessarily implies inefficiency and welfare burden;

(2) Our subjects are experienced decision-makers. While the precise characteristics of any individual file are unique, the setting in which they work and the broad parameters of case files are not novel. Furthermore, the setting mirrors the sort of repetitive-but-idiosyncratic decisions that agents such as consumers and managers face in the main economic models;

(3) The decision-makers that we observe work *indoors* and protected in their workplace by climate-control at a level typical of good-quality US Federal government buildings in the twenty-first century. In terms of protection, then, close to full application of the most obvious technological solution to mitigate temperature effects is already accounted for in the results. With regard to biological adaptation to prevailing conditions, judges move around very little - they are largely attached to a single court location - meaning that they are 'used to' the prevailing temperature patterns in the city in which we observe them.[2]

(4) The quality of data and the procedural details of the immigration system allow us to avoid a plethora of identification challenges, allowing for clean, persuasive causal inference.

Our main approach uses high frequency data to estimate a linear probability model with a variety of fixed effects, though we also provide some non-parametric results. In addition we develop variants in which the independent variables of interest are (a) the Heat Index (a measure used by the US National Weather Service that combines temperature and humidity non-linearly into a metric designed to capture how hot it 'feels') and, (b) the difference between realized temperature on a particular date and local norms for that date. Our central identifying assumption is minimal: That temperature realizations are as good as random after accounting for spatial and temporal fixed effects.

The analysis uncovers a substantial effect of short-term (daily) variations in temperature on decision outcomes. In our preferred specification, which include city-by-month and judge fixed effects, as well as controls for case characteristics and other potential environmental confounders, same-day outdoor temperature has an impact on decision outcomes. Our results suggest that a 10 °F degree increase in temperature reduces the likelihood of a decision favorable to the applicant by 1.075% which is equivalent to 6.55% decrease in the grant rate (the grant rate in the data as a whole is 16.4%). To put this into perspective, in our sample the difference in grant rate between a judge at the 25th percentile in terms of leniency, and one at the 75th percentile, is 7.9%. Consistent with

[2]Additionally, because location and dates of work are determined externally and in a way not sensitive to short-term temperature realizations we do not face complications due to displacement that might be important in other settings. For example, in some professions an employee might choose to defer work from a hot day to a cooler day (or work in the evening), or decide to work at home in response to weather conditions.

some existing studies of temperature susceptibility varying by gender (Yu et al. (2010), Xiong et al. (2015)) the effect is particularly pronounced for female judges. To allay concerns that there might be something unique to the immigration setting that is driving the results we repeat the exercise for decisions made in 18 461 Parole Suitability Hearings at the 39 locations of the California Department of Corrections and Rehabilitation (CDCR), arriving at parallel conclusions.

Why are these results important? As a straight piece of law and economics the research contributes to an assessment of the consistency of US immigration (and California parole) practices. The Sixth Amendment to the US Constitution lays out 'fair trial' as a fundamental right. Administrative Procedure Act (APA) (1946) determines that any adjudication or decision by an agent of the US government should not be "arbitrary or capricious". Agency decisions should be "... rationally connected to the facts before it" (Committee on Capital Markets Regulation (CCMR), 2016, p.2). The immigration court system is 'about' decisions, and natural justice - as well as the law - dictates that decisions on a particular file should be based solely on the merits of the case ("the facts and nothing but the facts"). There is no plausible reason why a particular file should have any different prospect of success if evaluated on a day unusually warmer for that location at that month-of-the-year, than on a day with a different temperature realization.[3]

However, as our opening paragraphs suggest, cautiously we propose that the analysis provides a *prima facie* case that temperature may damage decision consistency and quality in a much wider set of settings. If experienced, professional judges, working in an environment in which they are protected from outdoor temperature with high-quality climate control technology, are as subject to influence as our analysis suggests, what should we think might be the impact of temperature on the wider population of agents (consumers, investors, managers, etc.) making diverse decisions with long lasting implications for welfare?

We are careful not to over-interpret the results, but it is tempting to juxtapose the findings with what we know about differences in temperature profiles across locations and through time. That we do not observe 'right' and 'wrong' decisions, even ex post, precludes definitive welfare analysis. Given that the correct arbitration does not depend on contemporaneous temperature *the sensitivity of outcomes to changes in temperature in itself implies inefficiency.* However it is not possible for us to point to particular type 1 and 2 errors.[4] Notwithstanding this it is straight-forward to infer ballpark estimates

[3]There has been a very long and much broader body of debate on arbitrariness in legal systems in the US and elsewhere. Oakley and Coon (1986), Danziger et al. (2011).

[4]We do not have access to decision appeals which, at least superficially, might help identify errors. However, the rights to appeal and review in this area are much less developed than in those areas of law that relate to US citizens (which be construction immigration law does not). In addition, this is an area in which judges have wide discretion in interpreting case circumstances, and there is no right to appeal purely against how that discretion is exercised. Appeals (as in most areas of law) relate only to procedural errors.

for "excess" wrong decisions based on an additional *assumption*, grounded in existing research, that human comfort and performance is optimized at a particular temperature range.

The rest of the paper is laid out as follows. In Section 2 we provide a sketch of some existing research on the effect of temperature on humans, and the mechanisms that might underpin a link from outdoor temperature to indoor decision-making. Sections 3 and 4 detail data sources and methods. Section 5 presents the results of the main analysis and a series of robustness and falsification checks. Section 6 concludes.

2 Literature

While mechanism is not going to be our central focus it is worth highlighting several strands of research that link temperature to mental function, decision-making, risk attitudes and mood.

Several studies have examined the role of *indoor* temperature on some measure of mental or cognitive acuity. The temperature in a space is manipulated by the researcher, who then observes some measure of performance. For example, Hedge (2004) and Fang et al. (2004) examine performance on simple visual tasks and abstract problem solving in a laboratory. Wyon et al. (1996) assess vigilance, again in a temperature-manipulated laboratory setting. Chao et al. (2003) measure a set of more complex tasks in an office. Allen and Fischer (1978) measure student learning in classrooms. Seppanen et al. (2006) conduct a meta-analysis of the 24 papers that a particular search protocol elicits on this topic (including those just listed). Of these, 9 take place in the lab, the rest are in offices or schools, and between them they generate just over 100 effect size estimates. Their systematic review of the literature generates an estimate of the indoor temperature associated with highest productivity being at 21.75 °C (71.5 °F) with a decrement of performance of around 9% when temperature is 30 °C (86.1 °F).[5] In general heat stress has a much greater influence than does cold stress on the performance of cognitive tasks (see Hancock and Vasmatzidis (2003) for a review).

Turning to decision-making in particular, Cheema and Patrick (2012) present five studies of consumer behavior in which they manipulate laboratory temperatures. In higher temperatures subjects are; (a) less likely to engage in gambles (particularly complex gambles); (b) less likely to choose innovative products over established ones, and;

[5]The first of these numbers accords with anecdotal introspection. In a more recent review (Cheema and Patrick, 2012, page 985) note that: "Prior studies find that an ambient temperature of 72 °F, one at which most people appear comfortable, may be most conducive for automatic tasks". For instance, Allan et al. (1979) find that performance on a paired-association memory task peaks at 72 °F. Other evidence suggests a difference between temperatures that are optimal for comfort and those that are optimal for performance. Specifically, Pepler and Warner (1968) show that people perform office work best at 68 °F, although they report feeling cold."

(b) more likely to rely on "system 1" (heuristic or habit-based) processing (Pocheptsova et al. (2009)). In our setting - in which the rejection rate of immigration applications is around 83% such that the granting an applicant leave to stay can plausibly be regarded as the less-habitual, more innovative and more risky choice - this would point to a negative relation between high temperatures and grant rates.

While evidence of the effect of contemporaneous indoor temperature on brain-intensive tasks is suggestive for us, none of it is directly relatable. Studies that cast light on how daily *outdoor* temperature affects indoor mental performance are rare. Graff Zivin et al. (2018) find that (outdoor) temperature above 79 °F on a particular day damages performance of children on math (but not reading) tasks. Park (2016) investigates the relationship between daily outdoor temperature and high school exit exams in New York city and finds that compared to a 72 °F day, taking an exam on a 90 °F day reduces a typical student's performance by 0.19 standard deviations.

Turning away from cognition, separate strands of research evidence; (a) a causal link from ambient temperature (and other dimensions of weather) to 'mood', broadly defined, and then; (b) a causal link from mood to decision-making. Baylis (2015) links temperature to measures of hedonic state (mood) using geo-located Twitter activity. His four sentiment metrics based on phraseology, emoticon use and profanity each become more negative once outdoor temperatures exceed 70 °F (with little to no effect for colder temperatures). Denissen et al. (2008) find a similar effect when they analyze online diary entries of 1 233 students. Relatedly, a number of behavioral finance papers (for examples Hirshleifer and Shumway (2003), Cao and Wei (2005), Floros (2011)) link daily variations in weather - typically cloud cover and sunshine, but also temperature and humidity - to stock price movements via changes in emotional state.

With particular focus on judicial outcomes, Guthrie et al. (2007) discuss the role that emotion and cognitive overload can have on the decisions made by judges. Chen (2017) finds that the probability of a decision in favor of the applicant by US immigration judges increases by 1.4% the day after a win for the home NFL team. Eren and Mocan (2018) find that Louisiana juvenile court judges hand down sentences that are 6.4% longer following an unexpected loss by the Louisiana State University (LSU) NCAA football team, with the effects largest for judges who based closest to the home of LSU. Danziger et al. (2011) find that the likelihood of a favorable judgements by Israeli parole boards is higher after a food break. There are also various experimental papers identifying the unwanted influence of mood, cognition fatigue and emotion on judgment mor generally (Englich and Soder (2009), Simon (2012) Dijksterhuis et al. (1996) and Wyer and Carlston (1979)).

Turning to the question of this paper, the decision-maker in our setting is protected from outdoor temperature by climate control, but may 'import' the effect of exposure to, for example, an extreme outdoor temperature when they move inside, coming in from the morning commute, or after a break.[6] Determining the physiological mechanisms through which this happens is beyond the scope of our paper.[7] Outdoor conditions could in principle affect the output of the subject even *if he never went outside and was exposed to it.* For example, if external temperature is very high he might not venture outside during breaks 'for fresh air'. Anyone who has spent time in a city like Houston or Atlanta during a heat-wave should understand that possibility. Lack of fresh air has been linked to reduced cognitive function (Chen and Schwartz (2009)) and mood (Cunningham (1979)).

3 Data

Our central analysis links US-wide data on outcomes of asylum applications with what we know about environmental conditions at the location of decision on the date in question. We also use state-wide parole decisions from California to probe external validity.

3.1 Immigration

We use case-level administrative data on US asylum applications made to immigration courts from January 2000 through September 2004. Our final dataset includes the universe of 206 924 decisions made over this 58 month period by all 266 immigration judges across the 43 US cities in which courts are located (see Figure 1). Each court serves a specific geographical region. Decision data is merged with hand-collected data on judge gender. In our dataset, 34% of judges are female. The mean grant rate (the rate at which a decision is made that favors the applicant) in the database as a whole is 16%.

Our data comes from asylumlaw.org. Asylumlaw no longer operates but was: "A website run by an international consortium of agencies that helps asylum seekers in Australia, Canada, the United States and several countries in Europe. It provides links to legal and human rights resources, experts, and other information valuable for asylum seekers."[8] The data contains date of hearing, identity of judge, nationality of applicant and category of application.[9]

[6]We do not observe the time at which a particular file is adjudicated or know the movements of the judge during the day (when he or she is indoors, or outdoors) so cannot speak to intra-day variation. However the scheduling of files within the day is done many months in advance and therefore unrelated to temperature realizations.

[7]There is also research on the effect of ambient temperature on a variety of animal behaviors. We do not survey it here. However - for one example among many - Mathot et al. (2015) find that birds are less likely to engage in risky choices at higher-than-familiar temperatures. Elsewhere, Graff Zivin et al. (2018), p.2 note the existence of a more general ".. neurological literature that documents the brain's sensitivity to temperature".

[8]The dataset was kindly provided by Professor Kelly Shue (University of Chicago Booth School of Business) in personal correspondence.

[9]There are two types of cases in immigration courts: affirmative cases in which the applicant presents in the courts on her/his own and defensive cases in which the applicant is instructed to attend on the

Asylum decisions made by immigration judges are decisive and those that are denied asylum are subject to removal. Judges sit alone, and there are no formal quotas with respect to their grant rate. While the activities of judges are subject to the overall supervision of the US Attorney General, this is an area of law in which individual judges are widely regarded as having a high degree of personal discretion and independence in the way in which they evaluate files (see Ramji-Nogales et al. (2007) and Chen et al. (2016)). Though the characteristics of cases that judges in different locations are likely to see will of course vary, the degree of discretion is supported anecdotally by the wide variation in grant rates of judges both between and within particular courthouses. For instance, over the study period in the Los Angeles courthouse there are five judges that granted asylum to fewer than 4% while three others granted in over 67%.

Judges typically determine multiple cases on a given day. The judge is presented with a file, may (or may not) ask questions of the applicant, then enters an adjudication. Within a court all cases are in principle randomly assigned to the judges (Ramji-Nogales et al. (2007)), however we do not test for random assignment on observables, neither does our approach to identification rely on it. The setting of dates for cases and the rostering of judges is done well in advance. For instance, as of December 2016 more than 533 000 immigration cases had hearing dates scheduled, with the average delay from scheduling to hearing being over a year.

An important question is the extent to which adaptation might allow the impacts of temperature variations to be mitigated. The most obvious protective measures are building design and climate-control. As such it is useful to note in passing the context in which our subjects work. All of the courtrooms represented in the study are contained within climate-controlled buildings, as would be expected for important operational spaces of the US Federal government. Figure 2 contains pictures of the 16 largest locations ranked by contribution of cases to sample - contributing between them 86.4% of the total sample. While the buildings vary, taken as a set it is apparent that the judges work in good quality space, of the sort experienced by many North American professionals.[10] The effects of external temperature on internal behavior that we identify in this paper should be taken as already being adjusted for that level of adaptation embodied in buildings typical of this class.[11]

initiative of the immigration authorities.

[10]In an unreported robustness check we dropped venues one at a time and re-ran the preferred specification on the remaining sample. In no case did this substantially disturb the resulting estimates, implying that no single venue is driving results.

[11]In procuring space for judicial use the Administrative Office of the United States Courts (AOC) sets stringent standards for many dimensions of the space, including the quality of climate control. Courtrooms are pre-cooled to 70 °F degree before scheduled cases (Administrative Office of the United States Courts (AOC) (1996)).

3.2 Parole

Data on all parole hearings conducted by the Board of Parole Hearing (BPH) between 3 January 2012 and 18 December 2015 is from the California Department of Corrections and Rehabilitation (CDCR).[12] The dataset includes 18 461 hearing decisions made by 12 BPH commissioners across the 39 venues in California. Figure 3 maps hearing locations.

The Board of Parole is responsible for evaluating the risk to public safety from the release of inmates incarcerated for serious crimes. A positive decision by the BPH means that a prisoner is released, so these are high stakes decisions. Parole hearings are conducted in-person with the inmate and at a facility located within that inmate's prison. Sessions are scheduled one year before an inmate becomes eligible for parole and conducted by a panel of two members, a Board Commissioner and Deputy Commissioner (Kathryne et al. (2016)). The former is a non-expert appointed from a variety of professional backgrounds (law enforcement, academia, the military, politics) while the latter is a civil servant and expert in legal process. Formally the Commissioner is responsible for running the hearing and exercising discretion in determining outcome, while the Deputy Commissioner for legalities and post-release management of successful applicants. Despite this, that the panel comprises two members potentially complicates inference, obscuring *individual* decision-making. The grant rate in the dataset - the fraction of cases in which a decision is made that is favorable to the applicant - is 16.48%.

Our data contains the date of hearing, identity of panel members, inmate unique identifier, location of hearing, hearing type and outcome.[13]

3.3 Environment

Our main research question is whether the adjudication on a file responds to the outdoor temperature on the day on which it is evaluated. To accomplish this, we combine our decision dataset with temperature and a variety of other environmental controls.

The location of asylum decisions from which we construct our dependent variable is drawn from the 43 US cities in which the US Department of Justice operates immigration courthouses. These are widely dispersed (see Figure 1) and subject to diverse weather conditions.

The exact date and location of each decision is known which allows us to assign environmental measures (pollution and weather) to each. Temperature and other weather data is obtained from two sources. Hourly observations for air temperature, dew point, air pressure, precipitation and wind speed are retrieved from the National Oceanic and Atmospheric Administration (NOAA).[14] Data for cloud cover comes from the Northeast

[12] The data can be obtained from: http://www.cdcr.ca.gov/.

[13] There are two types of hearing that we consider: (1) Initial parole (which is scheduled one year before eligibility), (2) Subsequent parole that is scheduled if there is any consideration in the initial session.

[14] The data is obtained from: https://www.ncdc.noaa.gov/.

Regional Climate Center (NRCC).[15] Weather information is assigned to each courthouse location from the closest monitoring stations, in no case further than 20 miles away. The average distance between weather monitoring stations and courthouses is 9.35 miles with standard deviation of 6.33.

For our central specifications we work with averages computed for the period 6 AM to 4 PM each day. This is the period over which decision-makers are likely "up and about" - including travel to work, and work day. It excludes exposure that arise after courts close, which logically can have no effect on proceedings. Figure **??** plots the distribution of cases over 6 AM to 4 PM mean temperature categories for the study period (2000 to 2004) across locations in 10 °F bins. Most existing research on the effects of short-term temperature and pollution on a variety of outcome variables work with calendar-day data and, while we believe this to be an inferior approach, for purpose of comparison we also present analysis on that basis. In a further variant, that we do not report, we also conduct the exercise using 8-hour blocks (Midnight to 6 AM, 6 AM to 4 PM, 4 PM to midnight).

We will also be controlling for air quality conditions. Daily pollution data is published online by United States Environmental Protection Agency (USEPA).[16] The dataset includes daily measures of particulate matter less than 2.5 microns in width ($PM_{2.5}$), carbon monoxide (CO) and ozone (O_3) throughout the United States for the period of 2000 to 2004.

Table 1 presents summary statistics.

4 Methods

4.1 Empirical strategy

We estimate the following linear probability model:

$$g_{it} = \beta_0 + \beta_1 temp_{it} + W_{it}\beta_2 + P_{it}\beta_3 + X_{it}\beta_4 + \gamma_i + \Psi_{ct} + \theta_t + \epsilon_{it} \tag{1}$$

where g_{it} is a binary variable that takes the value one if the judge's decision in asylum application i on date t is granted, zero otherwise.

The key independent variable is the mean 6 AM to 4 PM temperature on the date the case is considered, $temp_{it}$. For most of our discussion β_1 is the coefficient of interest.

To allow for the possibility that other dimensions of weather rather than temperature might impact decisions, we include a vector of weather controls, W_{it}. It contains dew point temperature (a standard measure of humidity), precipitation, wind speed, air pressure and sky cover on date t, in the vicinity of the courthouse in which application i is adjudicated, all calculated on a 6 AM to 4 PM average basis. Pollution exposure can also influence

[15]The data is retrieved from: http://www.nrcc.cornell.edu/.
[16]The data is available at: https://aqs.epa.gov/api.

cognitive function, mood and/or decision-making (Archsmith et al. (2016), Chang et al. (2018), Lavy et al. (2016)). To allow for this possibility we include P_{it} which is a vector of pollution controls. It comprises mean daily measures of ozone (O_3), carbon monoxide (CO) and particulate matter ($PM_{2.5}$).

Court and case context can be expected to impact case outcomes (Chen et al. (2016)). We include a vector X_{it} of controls for a number of additional court and application characteristics. More specifically, we control for the category of application (affirmative or defensive) and nationality of applicant.[17] The vector γ_i contains judge fixed effects which control for any time invariant variations in judge leniency.[18] The vector θ_t includes time fixed effects; day of week to account for possible changes in decision patterns across the day of week and year fixed effects to control for aggregate trend in the data and also to account for the likelihood of hotter work days due, for instance, to climate change. Finally, Ψ_{ct} is a vector of city-by-month fixed effects.

Error terms may be spatially- and serially-correlated. In our preferred specification standard errors are clustered by city-month which serves two purposes: to account for spatial correlation across cities and to allow for autocorrelation in decisions in each month. For the purposes of robustness we establish later that the results are robust to a variety of other ways of calculating standard errors.[19]

As noted we include a rich set of fixed effects. Importantly, we include judge fixed effects is all of our main specifications, allowing for systematic differences in decisions between judges. Primarily we are identifying off within-location, within-month variation. Our identifying assumption is that once location and time effects are controlled for, the realization of outdoor temperature on any *particular* day - and therefore the assignment of a temperature treatment to any particular decision - is as good as random.[20] That is to say, we can examine cases heard in Atlanta in June. But sometimes a case may

[17]The case characteristics that we observe are limited. It is clear that other unobserved characteristics are important determinants of case outcomes such that we have omitted variables. However, controlling for location and time fixed effects it is plausible that those omitted characteristics would be uncorrelated with case-day temperature such that the OLS estimate of β_1 would be unbiased and the associated standard error remains undisturbed.

[18]Judges are appointed to a specific court and that court is where they adjudicate the vast majority of their cases. However, they may occasionally be reassigned to another location for a short period. In our sample 168 of the judges adjudicated at least one case away from the court to which they were appointed (in total 12 245 of the 206 924 are heard by a judge away from his or her 'home' location). Excluding these cases has no discernible impact on results.

[19]In Table A.3 we present standard errors from nine alternative clustering strategies (columns (1) through (7)) and heteroskedasticity-consistent Eicker-White and Newey-West standard errors (columns (8) and (9)). In all cases the level of significance of the estimated coefficient is unchanged. While alternative clustering makes little difference the Eicker-White and Newey-West standard errors can be seen to be around 30% smaller, implying that our preferred approach can be regarded as conservative.

[20]To test our exogeneity assumption we re-estimate our preferred specification replacing decision outcomes as the regressand with, in turn, (1) the probability that an application is of type affirmative, (2) the probability that the adjudicating judge is female, (3) the probability that the applicant has a Middle Eastern country of origin and, (4) the total number of cases heard by a judge on that day. In each case we find no significant relationship. Results are presented in Table A.4 and Figure A.1.

be assigned a temperature treatment of 60 °F, other times 90 °F. It is that variation, plausibly exogenous, that we exploit for identification.

5 Results

5.1 Linear

The base results are summarized in Table 2. Column (1) is the preferred specification, incorporating the full suite of controls - time fixed effects, weather and pollution controls.[21]

The coefficient in column (1) is -1.075 implies that a 10 °F increase in 6 AM - 4 PM temperature on the day a decision is made reduces the likelihood of a grant decision by 1.075%. Recall that the average grant rate in the sample is 16.4%, so this implies a 6.55% decrease in grant rate. The effect of a 10 °F rise in temperature is comparable in size to those found by Eren and Mocan (2018) for an unexpected loss by the local NCAA football team (which induced a temporary 6.4% increase in severity of juvenile sentencing). Several studies point to between-judge variation in asylum grant rates (Ramji-Nogales et al. (2007) and Chen (2017)). In our sample, the difference in grant rate between a judge at the 25th percentile in terms of leniency, and one at the 75th percentile, is 7.9%.

Columns (2) and (3) of Table 2 report the results of including lag or lead. In each case the point estimates on the lagged terms are much smaller in absolute value than those on the main measure, mixed in sign, and never approach significance at conventional levels. Column (4) includes both lead and lag terms. Figure 5 plots results when we add three lags and three leads simultaneously. As can be seen, none of the lags or leads achieve significance.[22] The F-statistic of joint significance of weather variables reported at the bottom panel of Table 2 rejects the null hypothesis of no effect for weather covariates treated jointly.[23]

Our main specification incorporates what we believe to be the most natural set of time fixed effects (year and city-month). However Table 3 reports the results of other approaches. In columns (1) through (6) we build up to the preferred specification by adding fixed effects in sequence while columns (7) to (9) present four other plausible alternatives. Column (10) repeats the preferred specification for purposes of comparison. The addition

[21] All of our main specifications are estimated on the whole 58 months of data. The terrorist attacks of 11 September 2001 fall during our study period and can be expected to have impacted on the operation of the immigration system in the US. While we do not report them here, we have run the main specifications on the pre- and post-9/11 portions of the data-set, observing consistent patterns across them.

[22] We repeat the exercise replacing decision outcome with (1) type of application and, (2) total number of cases heard by a judge on a given day. Results are summarized in Figure A.2 and reveal no significant effect of leads or lags of temperature on these observables.

[23] Table A.1 presents point estimates for all environmental variables included in the preferred specification.

of city-by-month fixed effects in column (6) brings point estimates close to those form the preferred specification (-1.037 compared to -1.075) suggesting the importance of seasonal patterns.

To facilitate comparison, in the lower panel of Table 3 we also present Hausman statistics that in each case allow us to reject the null hypothesis of a significant difference between the estimated coefficient of interest in that column and that in the preferred specification. The stability of the estimated coefficient on temperature to so many alternative permutations of fixed effects is reassuring.

Table 4 explores the sensitivity of results to some alternative but plausible specifications.

Much of the related literature on short-term effects of weather and air quality on human outcomes has used the calendar day as its unit of analysis (for examples, Hirshleifer and Shumway (2003), Lavy et al. (2016) and Park (2016)). While this is not our preferred approach - a substantial portion of each calendar day occurs after the court is closed, for example - for comparability we report in Table 4, column (2) the results of repeating the exercise on a calendar day basis. As would be expected given the introduction of additional imprecision into the way in which the regressor of interest is measured, the estimated coefficients are attenuated somewhat, but retain sign and significance and are similar in magnitude to Table 2 (-0.750 instead of -1.075 for the preferred specifications).[24]

Decision locations are dispersed widely across the country and in places that exhibit very different weather patterns. This implies that a 90 °F degree day in Phoenix may not have the same effect as such a day in Boston. The inclusion of city-month and year fixed effects should control for unobservable characteristics of that location at that time of year (such as "normal" weather conditions). However to probe this further we estimate a variant in which the independent variable of interest is the deviation of 6 AM - 4 PM temperature on decision day from the average 6 AM - 4 PM temperature for that location in that week of the year. The results of this exercise are summarized in column (3). The point estimate on same-day temperature deviation is negative and significant at 5%.

The results of an additional exercise to address the concern that the impact of a given temperature treatment may vary by location is reported in column (4). Here we re-estimate the preferred specification but now incorporating a vector of *city* x *temperature* interaction terms, with New York chosen as our reference city. Point estimates on 40 out of the 44 interaction terms are insignificant. As can be seen, inclusion of the interaction terms does not substantially disturb our conclusions.

Most of the evidence that we present points to the depressing effect of hot days on affirmative decisions (this will be confirmed in the non-parametric results that follow).

[24]In a further variant we conducted the exercise using 8-hour blocks (Midnight - 8 AM, 8 AM - 4 PM, 4 PM - midnight). The results (not reported here) parallel those presented.

Much of the US is cold during the winter months, while the whole mainland is mild to hot during the rest of the year. Column (5) reports the results of re-estimating the preferred specification but excluding the winter months. Again, the coefficient on temperature retains sign and significance, though it is now somewhat larger in absolute value.

To further confirm the mechanism of influence, in column (6) we perform another robustness check by including interaction term of *precipitation* and *temperature* into our preferred specification. As shown the point estimate on temperature is negative and significant at 5% while the interaction term is statistically insignificant at conventional levels.

In an additional exercise we explore the role of gender of judge. For this exercise we re-estimate the preferred regression specifications on the sub-sample of decisions made by female judges (72 229 decisions made by 95 individuals) and male judges (134 695 decisions made by 171 individuals) separately. In Table A.2 the results of these exercises are summarized in columns (2) and (3) respectively. In each case the point estimate is negative and significant at the 5% level. However the female coefficient is around 6% bigger in absolute value. The Hausman test (reported in the lower panel of Table A.2) confirms that the coefficient values are significantly different at the 5% level (p-value 0.0325). This is consistent with prior research that temperature-sensitivity is particularly pronounced amongst females (Yu et al. (2010), Xiong et al. (2015)). The result also goes some way to address a concern that the patterns that we observe are driven not by the effect of temperature on judgement, but that temperature is instead influencing outcomes by impacting (for example) the comportment of the applicant or his lawyer. If that (or other external-to-judge mechanisms) were the channel we would not expect to see differences based on gender of judge.

5.2 Non-linear

In addition to the conventional linear estimate we also examine possible of non-linearity in the relationship between temperature and decision outcomes by re-estimating using temperature bins 5 °F in width, with the 50 - 55 °F bin as the reference category.

The results of this exercise are presented in column (1) of Table A.2 and illustrated in Figure 6. Point estimates are statistically significant and positive when temperature is in the range of 25-30 and 40-45 and negative when it exceeds 55 °F. They are also meaningful in size. Other things equal, taking a case heard on a day where outdoor temperature is between 50 - 55 °F and dropping it instead into a day where the temperature exceeds 85 °F reduces the likelihood of a favorable decision by 6.31%.

The negative effects of temperature appear close-to-linear and most of the robustness checks and other exercises that we conduct below will be centred on the linear results.

5.3 Robustness

Table 6 reports the results of a battery of robustness tests.

5.3.1 Pollution

Recent research points to a possible link from short-term pollution exposure to mood and cognitive function, either of which might influence decision outcomes (Heyes et al. (2016) and Szyszkowicz et al. (2010)). While our main specifications include controls for ambient levels of the main pollutants (O_3, $PM_{2.5}$ and CO), concern may remain that we have failed to control adequately for air quality effects, and that these are confounding our results. If that were the case then we would expect dropping the whole set of pollution controls to substantially affect our estimate of β_1. In column (2) we report the result of re-estimating the preferred specification but omitting the vector of pollution controls. The estimated coefficient on temperature retains sign and significance and value changes only a little (-0.910 instead of -1.075).

5.3.2 California

Of our 43 venues 6 are located in California (accounting for around 32% of all decisions). To rule out that what we are picking up something idiosyncratic to California - particularly since our external validity exercise is going to rely on Californian parole data - we re-estimate our preferred specification excluding decisions made at courts in that state. This excludes around 71 000 of the 207 000 decisions in sample. The result of this exercise are reported in column (3) of Table 6. Again, when estimated on the restricted sample the estimate of β_1 retains sign and significance and is little-changed in value (-1.159 instead of -1.075). So the pattern that we observed in the data is not being 'driven' by anything particular to California.

5.3.3 Weather

Columns (4), (5) and (6) probe further the potential confounding role of rain and cloud.

Existing research points to cloud cover as influencing mood (Lambert et al. (2002), Kent et al. (2009) and Hirshleifer and Shumway (2003)). We include a continuous variable that captures extent of cloud cover in our main specification to control for this. However, as a further test we re-estimate the central specification on those decisions made on "clear sky" days - the subset of days when daily cloud cover is less than 5% (results in column (4)). The point estimate of β_1 for the subsample estimation remains negative and significant. Though larger in absolute value (-2.738 instead of -1.075), suggesting that elevated temperature has a more pronounced impact on decision on blue sky days versus non-such days, the difference between the two values is not significant at the 5% level.

Similarly rain can influence mood (Denissen et al. (2008)). While a continuous measure of precipitation is included in the vector of weather controls, column (5) reports the result of re-estimating the preferred specification on the subset of decisions (133 890 of them) made on days in which local recorded precipitation is zero. On such days rain cannot plausibly be argued to have influenced outcomes. The estimated coefficient retains sign and significance and is changed slightly in absolute value (-1.304 compare to -1.075). Column (6) reports the results of pushing this further by repeating the same exercise this time excluding days on which recorded precipitation on either the day of decision or the day before were non-zero (111 361 decisions). Again the point estimate on the coefficient of interest is somewhat larger in absolute value (-1.281 instead of -1.075) but retains sign and significance.

5.3.4 Heat Index (HI)

The way in which temperature is experienced by the human body can itself depend on the water content of the air. Humidity is known to affect both mood and labor productivity (Howarth and Hoffman (1984), Tsutsumi et al. (2007) and Wan et al. (2009)). We therefore investigate the joint effect of temperature and humidity in our setting by dropping temperature and dew point from our preferred specification and replacing it with the Heat Index (HI). The HI is used by the US National Weather Service and combines air temperature and relative humidity, via a non-linear algorithm, into a single metric designed to capture how hot it 'feels'. It effectively adjusts upwards the dry air temperature for moisture content to provide an index of the discomfort associated with a particular temperature/humidity combination.[25]

Column (7) reports the results of re-estimating our preferred specification but with HI added, temperature and dew point dropped. Consistent with earlier results we find a negative and significant effect of heat index on decision outcomes. Though the coefficient here is not directly comparable to those from the various other specifications, the point estimate implies that a 10 degree F increase in HI reduces the probability of grant decision by 0.44% (recall that this is against an average grant rate in the sample of 16.4%). However, since HI is primarily regarded as a reliable measure of discomfort only in warm conditions, we also conduct this exercise once more on the subsample of days on which the local heat index exceeds 75 °F in column (8). The estimated coefficient on heat index is negative and significant with an absolute value larger than in column (7), though estimated on a much smaller sample.

In Figure 7a and column (2) of Table A.2 we repeat this exercise for the HI variant

[25] Countries including the UK and France have an alternative index - called Humidex - that has the same intention, and is highly correlated with HI, but is calculated by a slightly different formula. HI and Humidex references are often heard on media weather broadcasts during warmer times of year. The HI is typically seen as relevant or reliable measure only in warm conditions.

of the analysis - with dew point temperature and temperature omitted as regressors but HI added. As noted, this provides a plausible way for allowing for the combined effects of temperature and humidity on how heat is actually experienced (how it 'feels'). Since HI is only regarded as reliable on warmer days, Column (3) of Table A.2 and Figure 7b repeat the same exercise for the subsample of days on which HI exceeds 65 °F, with the 65 - 70 °F bin as the reference category. Again the negative impacts of HI exhibit a close to linear pattern with the negative effect become significant for values of HI exceeding 80 °F.

5.3.5 Outlier judges

We note in the data section that judges do not have specific quotas with respect to what their grant rates should be - indeed this is an area of the legal system in which judges, sitting alone, are regarded as exercising a very high degree of personal discretion (Ramji-Nogales et al. (2007)). To convince ourselves that the result that we are claiming is not being driven by 'extreme' judges we conduct two outlier analyses.[26] In the first we exclude those decisions made by judges who have a grant rate across the whole study period in either the top or the bottom quartile (just retaining the 'middle half' of judges when ranked in terms of moderation).[27] Column (9) reports the results of this exercise - again sign and significance is retained and the value of the coefficient is little disturbed (-0.707 instead of -1.075). In the second we conduct the same exercise but exclude the top and bottom deciles of judges.[28] The results of this is reported in column (10). Again the sign and significance is retained and the value of the coefficient is little disturbed (-1.064 instead of -1.075).

5.4 Placebos

As further falsification tests we perform three placebo exercises.[29] First, we replace the decision-day temperature series with the temperature at the same location 100 days after decision-day, and 100 days before. Second we replace the decision-day temperature in the vicinity of the courthouse in which the decision was made with the temperature on the same day, but taken from the weather monitoring station *most distant from it* "as the

[26]For example, suppose there existed a judge who is so extreme that he never found in favor of the applicant (his grant rate was 0%). The grant rate of that judge could not go lower upon exposure to high temperature because he is already at the lower bound. Recall that we already have judge fixed effects in all of our main specifications.

[27]This excludes decisions made by judges who have overall grant rates below 8.1% or above 22%.

[28]This excludes decisions made by judges who have overall grant rates below 4.7% or above 31%. Note that while we exclude the top and bottom decile of judges we do not lose exactly 20% of our sample of decisions. This is because different judges are associated with different numbers of decisions across the study period.

[29]For this exercise we limit analysis to mainland US locations (exclude weather stations in Puerto Rico and Hawaii). We ran a wide variety of other placebos with similar (insignificant) results.

crow flies". For example, for Hartford (Connecticut) the placebo temperature is taken from the NOAA measuring station at Davenport (California) 4238.72 miles away; for Dallas (Texas) the placebo temperature values are taken from Port Angeles (Washington) 2792.42 miles away.

The results of these exercises are reported in Table 7. In each case the absolute value of the estimate of the coefficient of interest is several times smaller, signs are mixed and in no case is statistical significance achieved.

5.5 Parole

Until now we have focused on judges evaluating immigration files. We are not going to claim broad generality of results, though we believe they are highly suggestive of what is likely to be a wider phenomenon. However to probe at least a little into whether the effects that we have identified are unique to the immigration setting we repeat the central linear and non-parametric analysis for decisions made by parole commissioners in the context of Californian parole hearings.

Table 8 presents results that repeat the main part of our analysis on a calendar day basis using results from the universe of hearings for the period of 3 January 2012 to 18 December 2015 (18 461 in total) as dependent variable. More concretely the dependent variable is a dummy that takes the value one if a parole applicant is granted release, zero otherwise.

The pattern of results presented in Table 8 proves similar to those earlier. Decision-day outdoor temperature has a significant, negative effect on likelihood of a decision to release the applicant. The effect is similar in magnitude to the immigration setting. In the preferred specification (column (1)) a 10 °F degree increase in outdoor temperature reduces the probability of a grant release decision by 1.56%. Against an average grant rate in the data-set of 16.48% this implies a 9.5% decrease in the rate of affirmative decisions. We also test the implications of adding a single lag or lead, both individually and concurrently (columns (2), (3) and (4)), again finding coefficients on these that are much smaller, mixed in sign, and never achieve significance. That their inclusion or exclusion disturbs the estimated coefficient of interest more than in the immigration case likely reflects the lower day-to-day variation in the mid to southern Californian locations of the hearing venues.

Figure 8 depicts the results of non-parametric analysis applied to this setting. Point estimates are negative and statistically significant at 5% for temperatures exceeding 65 °F. Consistent with the results from the immigration setting, there is close to linear effect of temperature on decision outcomes. Results suggest that compared to a day with average temperature in the 50 to 55 °F bin, the likelihood of releasing an inmate is 2.6% lower on a day when temperature is higher than 85 °F. In the context of an overall grant rate of 16.48% this corresponds to a 15.8% fall in the rate of decisions favoring the applicant - a substantial effect.

6 Conclusions

Temperatures vary across space and through time. We present what we believe to be the first evidence - in either a naturally-occurring or artificial setting - that same-day outdoor temperature influences indoor decisions. The results extend the finding that outdoor temperature affects the test performance of students (for example Park (2016)) to a high-stakes, workplace 'cognitive output'. Effect sizes are large and robust. Our central estimate is that a 10 °F degree increase in temperature reduces the likelihood of a decision favorable to the applicant by 1.075% which is equivalent to 6.55% decrease in the grant rate (the grant rate in the data as a whole is 16.4%). To put this into perspective - and recollecting that this is an area of law where judicial discretion is substantial, and it is acknowledged that judges exercise that discretion in quite different ways - hypothetically reassigning a case from a judge at the 25th percentile in terms of leniency, to one at the 75th percentile decreases the grant rate by 7.9%. That we study a naturally-occurring setting populated by experienced subjects adds to the likelihood that the effects identified reflect a broader phenomenon.[30] While the evaluation of a file may be sensitive to the case-day behavior of the applicant, and we cannot rule out that part of the effect that we uncover works through induced changes in that, the heterogeneity of effect between male and female judges points to an internal–to-judge effect. If this was purely a story about over-heated applicants changing their comportment, we would not expect the gender of judge in a particular case to matter.

While we don't observe their precise movements nor some other particularities of the indoor conditions in which they work, we can say that this group of professionals work in good quality, climate-controlled environments. Also, presumably, they travel to work and move around their cities in a manner consistent with better off professional workers (have air conditioning in their cars, *etc.*). In other words, the subjects that we study are offered a level of protection against weather variations that most people, even office-based professionals, would find quite comprehensive. That despite this we still observe substantial and robust effects of ambient temperatures outdoors to how these individuals are going about their business indoors, makes a case against claims that climate control can be (fully-) effective in ameliorating climate impacts.

There are different ways to think about the implications of the results. At the broadest, we provide a bridge from local climate to what is happening indoors - where most high value employment is based, and where most important work and non-work decisions

[30]The parole results provided some 'out of sample' testing, and reassurance that the patterns that we see in the immigration data are not unique to that setting.

are taken - even when the agents, and the buildings in which they work, are adapted to local conditions.

As such we can, amongst other things, provide a plausible link from local climate to workplace productivity. Of course we rarely have persuasive measures of individual, daily productivity in high value employment settings (which is why existing research has focused on low-grade jobs such as picking fruit and answering routine calls in a job center). Our setting shares that shortcoming since the job of a judge is quality-driven and we do not observe 'right' and 'wrong' decisions, even ex post. However, given that the correct arbitration self-evidently does not depend on contemporaneous temperature *the sensitivity of outcomes to changes in temperature in itself implies welfare inefficiency*. Insofar as the correct arbitration matters - in other words that this is from a societal perspective of a high-stakes setting - the large effect sizes imply that the welfare losses are, in turn, large.

Away from the world of work, decisions are central to human well-being. We all routinely make decisions about what to buy, how to invest, how to vote, when to quit our jobs, etc. If decisions with durable impacts are systematically affected by irrelevant, transient factors then the potential for individual and welfare loss across many settings is obvious.

One area in which we have been agnostic throughout the paper is channels. Pinning down the mechanism(s) from outdoor temperature to indoor decision processes would be a useful ambition of future work, and probably initially best suited to laboratory or laboratory-in-the-field methods. The two broad channels that we noted in the introductory review that are consistent with the results relate to (1) mood and (2) cognitive acuity. High temperatures may stimulate temper, irritability (for example in Baylis (2015) Twitter users are more likely to use profanity) and other emotions that might induce a judge to be less well-disposed towards a typical applicant. In addition depressive mood has been linked to reduced risk appetite. In both the immigration and parole settings denying a request can be plausibly be regarded as the risk averse course of action. Mental fatigue and other effects of heat can reduce mental acuity which can increase mistakes, and also themselves induce transient increases in risk aversion.

Just as we have sought not to over-sell the results, neither should we over-state the limitations. It is widely-believed that world average temperatures are rising, as are the frequency of very hot and very cold days. Understanding the full set of social and economic outcomes that extreme temperature can influence is crucial to forming a measured view of the implications of such climate change. That outdoor temperature can have a large, significant and apparently robust effect on indoor decisions, even when subjects operate in a climate-controlled setting, has potential for how we think about the links from climate to human well-being. The bounds on those effects, and the mechanisms underpinning them, are important foci of ongoing research.

Bibliography

Abd-Elfattah, H. M., Abdelazeim, F. H., and Elshennawy, S. (2015). Physical and cognitive consequences of fatigue: A review. *Journal of Advanced Research*, 6(3):351–358.

Administrative Office of the United States Courts (AOC) (1996). Standard Level Features and Finishes for U.S. Courts Facilities. `https://www.wbdg.org/FFC/GSA/slff.pdf`. Accessed: 2017-09-27.

Administrative Procedure Act (APA) (1946). The Administrative Procedure Act (United States): Pub.L. 79–404, 60 Stat. 237. `http://www.legisworks.org/congress/79/publaw-404.pdf`. Accessed: 2017-01-21.

Ahn, H.-K., Mazar, N., and Soman, D. (2010). Being hot or being cold: The influence of temperature on judgment and choice. *NA-Advances in Consumer Research*, 37(1):85–88.

Allan, J. R., Gibson, T. M., and Green, R. G. (1979). Effect of induced cyclic changes of deep body temperature on task performances. *Aviation, Space, and Environmental Medicine*, 50(6):585–589.

Allen, M. A. and Fischer, G. J. (1978). Ambient temperature effects on paired associate learning. *Ergonomics*, 21(2):95–101.

Archsmith, J., Heyes, A., and Saberian, S. (2016). Air quality and error quantity: Pollution and performance in a high-skilled, quality-focused occupation. Technical report, Unpublished Manuscript UC Davis Economics.

Ariely, D. and Loewenstein, G. (2006). The heat of the moment: The effect of sexual arousal on sexual decision making. *Journal of Behavioral Decision Making*, 19(2):87–98.

Baron, R. A. and Bell, P. A. (1976). Aggression and heat: The influence of ambient temperature, negative affect, and a cooling drink on physical aggression. *Journal of Personality and Social Psychology*, 33(3):244–245.

Baylis, P. (2015). Temperature and temperament: Evidence from a billion tweets. Technical report, Energy Institute at HAAS Working Paper 265.

Cao, M. and Wei, J. (2005). Stock market returns: A note on temperature anomaly. *Journal of Banking and Finance*, 29(6):1559–1573.

Chang, T., Zivin, J. G., Gross, T., and Neidell, M. (2018). The effect of pollution on worker productivity: Evidence from call-center workers in China. *American Economic Journal: Applied*, (Forthcoming).

Chao, H., Schwartz, J., Milton, D., Muillenberg, M., and Burge, H. (2003). Effects of indoor air quality on office workers' work performance–a preliminary analysis. *Proceedings of Healthy Buildings*, 3(4):237–243.

Cheema, A. and Patrick, V. M. (2012). Influence of warm versus cool temperatures on consumer choice: A resource depletion account. *Journal of Marketing Research*, 49(6):984–995.

Chen, D., Moskowitz, T. J., and Shue, K. (2016). Decision-making under the gambler's fallacy: Evidence from asylum judges, loan officers, and baseball umpires. *Quarterly Journal of Economics*, 131(3):1181–1241.

Chen, D. L. (2017). Mood and the malleability of moral reasoning. Technical report, TSE Working Paper, n.16-707.

Chen, J.-C. and Schwartz, J. (2009). Neurobehavioral effects of ambient air pollution on cognitive performance in US adults. *Neurotoxicology*, 30(2):231–239.

Clore, G. L. and Huntsinger, J. R. (2007). How emotions inform judgment and regulate thought. *Trends in Cognitive Sciences*, 11(9):393–399.

Committee on Capital Markets Regulation (CCMR) (2016). Nothing but the facts: The regulatory reform process. `http://www.capmktsreg.org/wp-content/uploads/2016/11NBTF_Regulatory_Reform_.pdf`. Accessed: 2017-01-21.

Cunningham, M. R. (1979). Weather, mood, and helping behavior: Quasi experiments with the sunshine samaritan. *Journal of Personality and Social Psychology*, 37(11):1947–1956.

Danziger, S., Levav, J., and Avnaim-Pesso, L. (2011). Extraneous factors in judicial decisions. *Proceedings of the National Academy of Sciences*, 108(17):6889–6892.

Denissen, J. J., Butalid, L., Penke, L., and Van Aken, M. A. (2008). The effects of weather on daily mood: A multilevel approach. *Emotion*, 8(5):662–635.

Diamond, P. and Vartiainen, H. (2012). *Behavioral economics and its applications*. Princeton University Press.

Dijksterhuis, A., Van Knippenberg, A., Kruglanski, A. W., and Schaper, C. (1996). Motivated social cognition: Need for closure effects on memory and judgment. *Journal of Experimental Social Psychology*, 32(3):254–270.

Englich, B. and Soder, K. (2009). Moody experts—How mood and expertise influence judgmental anchoring. *Judgment and Decision Making*, 4(1):41–50.

Eren, O. and Mocan, N. (2018). Emotional judges and unlucky juveniles. *American Economic Journal: Applied*, (Forthcoming).

Fang, L., Wyon, D., Clausen, G., and Fanger, P. O. (2004). Impact of indoor air temperature and humidity in an office on perceived air quality, SBS symptoms and performance. *Indoor Air*, 14(7):74–81.

Ferrarelli, L. K. (2016). Hunger signals suppress risk perception. *Science Signaling*, 9(458):292–293.

Floros, C. (2011). On the relationship between weather and stock market returns. *Studies in Economics and Finance*, 28(1):5–13.

Graff Zivin, J. S., Hsiang, S. M., and Neidell, M. J. (2018). Temperature and human capital in the short-and long-run. *Journal of the Association of Environmental and Resource Economists*, 5(1):77–105.

Guthrie, C., Rachlinski, J. J., and Wistrich, A. J. (2007). Blinking on the bench: How judges decide cases. *Cornell Literature Review*, 93(1):1–45.

Halleröd, B. and Larsson, D. (2008). Poverty, welfare problems and social exclusion. *International Journal of Social Welfare*, 17(1):15–25.

Hancock, P. and Vasmatzidis, I. (2003). Effects of heat stress on cognitive performance: The current state of knowledge. *International Journal of Hyperthermia*, 19(3):355–372.

Hedge, A. (2004). Linking environmental conditions to productivity. *Power Point presentation. Eastern Ergonomics Conference and Exposition.*

Heyes, A., Neidell, M., and Saberian, S. (2016). The effect of air pollution on investor behavior: Evidence from the S&P 500. Technical report, National Bureau of Economic Research 22753.

Hirshleifer, D. and Shumway, T. (2003). Good day sunshine: Stock returns and the weather. *The Journal of Finance*, 58(3):1009–1032.

Howarth, E. and Hoffman, M. S. (1984). A multidimensional approach to the relationship between mood and weather. *British Journal of Psychology*, 75(1):15–23.

Jahedi, S., Deck, C., and Ariely, D. (2016). Arousal and economic decision making. *Journal of Economic Behavioral Organization*, 134(11):165–189.

Kahol, K., Leyba, M. J., Deka, M., Deka, V., Mayes, S., Smith, M., Ferrara, J. J., and Panchanathan, S. (2008). Effect of fatigue on psychomotor and cognitive skills. *American Journal of Surgery*, 195(2):195–204.

Kathryne, M. Y., Debbie, M., and Favre-Bulle, T. (2016). Predicting parole grants: An analysis of suitability hearings for California's lifer inmates. *Federal Sentencing Reporter*, 28(4):268–277.

Kent, S. T., McClure, L. A., Crosson, W. L., Arnett, D. K., Wadley, V. G., and Sathiakumar, N. (2009). Effect of sunlight exposure on cognitive function among depressed and non-depressed participants: A REGARDS cross-sectional study. *Environmental Health*, 8(1):34–36.

Lambert, G., Reid, C., Kaye, D., Jennings, G., and Esler, M. (2002). Effect of sunlight and season on serotonin turnover in the brain. *Lancet*, 360(9348):1840–1842.

Lavy, V., Ebenstein, A., and Roth, S. (2016). The impact of short term exposure to ambient air pollution on cognitive performance and human capital formation. *American Economic Journal: Applied Economics*, 8(4):36–65.

Loewenstein, G. (1996). Out of control: Visceral influences on behavior. *Organizational Behavior and Human Decision Processes*, 65(3):272–292.

Mani, A., Mullainathan, S., Shafir, E., and Zhao, J. (2013). Poverty impedes cognitive function. *Science*, 341(6149):976–980.

Mathot, K. J., Nicolaus, M., Araya-Ajoy, Y. G., Dingemanse, N. J., and Kempenaers, B. (2015). Does metabolic rate predict risk-taking behaviour? A field experiment in a wild passerine bird. *Functional Ecology*, 29(2):239–249.

Oakley, J. B. and Coon, A. F. (1986). The federal rules in state courts: A survey of state court systems of civil procedure. *Washington Law Review*, 61(5):1367–1368.

O'Brien, E. M. and Mindell, J. A. (2005). Sleep and risk-taking behavior in adolescents. *Behavioral Sleep Medicine*, 3(3):113–133.

Page, L. A., Hajat, S., and Kovats, R. S. (2007). Relationship between daily suicide counts and temperature in England and Wales. *The British Journal of Psychiatry*, 191(2):106–112.

Park, J. (2016). Temperature, test scores, and educational attainment. Technical report, Unpublished Manuscript University of Harvard Working Paper.

Pepler, R. D. and Warner, R. (1968). Temperature and learning: An experimental study. *Transactions of the ASHRAE Annual Meeting*, 42(2):211–219.

Pflug, B., Erikson, R., and Johnsson, A. (1976). Depression and daily temperature. *Acta Psychiatrica Scandinavica*, 54(4):254–266.

Pocheptsova, A., Amir, O., Dhar, R., and Baumeister, R. (2009). Deciding without resources: Psychological depletion and choice in context. *Journal of Marketing Research*, 46(3):344–355.

Ramji-Nogales, J., Schoenholtz, A. I., and Schrag, P. G. (2007). Refugee roulette: Disparities in asylum adjudication. *Stanford Law Review*, 60(2):295–411.

Seppanen, O., Fisk, W. J., and Lei, Q. (2006). Room temperature and productivity in office work. *Proceeding of Healthy Buildings Congress*, 1(1):243–247.

Simon, D. (2012). *In doubt: The psychology of the criminal justice process*. Harvard University Press.

Stern, N. H. (2007). *The economics of climate change: The Stern review*. Cambridge University Press.

Szyszkowicz, M., Willey, J. B., Grafstein, E., Rowe, B. H., and Colman, I. (2010). Air pollution and emergency department visits for suicide attempts in Vancouver, Canada. *Environmental Health Insights*, 4(1):79–86.

Tchen, N., Juffs, H. G., Downie, F. P., Yi, Q.-L., Hu, H., Chemerynsky, I., Clemons, M., Crump, M., Goss, P. E., Warr, D., Tweedale, M., and Tannock, I. (2003). Cognitive function, fatigue, and menopausal symptoms in women receiving adjuvant chemotherapy for breast cancer. *Journal of Clinical Oncology*, 21(22):4175–4183.

Tsutsumi, H., Tanabe, S.-i., Harigaya, J., Iguchi, Y., and Nakamura, G. (2007). Effect of humidity on human comfort and productivity after step changes from warm and humid environment. *Building and Environment*, 42(12):4034–4042.

Viner, R. M., Clark, C., Taylor, S. J., Bhui, K., Klineberg, E., Head, J., Booy, R., and Stansfeld, S. A. (2008). Longitudinal risk factors for persistent fatigue in adolescents. *Archives of Pediatrics and Adolescent Medicine*, 162(5):469–475.

Wan, J., Yang, K., Zhang, W., and Zhang, J. (2009). A new method of determination of indoor temperature and relative humidity with consideration of human thermal comfort. *Building and Environment*, 44(2):411–417.

Weaver, L. J. and Hadley, C. (2009). Moving beyond hunger and nutrition: A systematic review of the evidence linking food insecurity and mental health in developing countries. *Ecology of Food and Nutrition*, 48(4):263–284.

Weinreb, L., Wehler, C., Perloff, J., Scott, R., Hosmer, D., Sagor, L., and Gundersen, C. (2002). Hunger: Its impact on children's health and mental health. *Pediatrics*, 110(4):41–50.

Williams, L. E. and Bargh, J. A. (2008). Experiencing physical warmth promotes interpersonal warmth. *Science*, 322(5901):606–607.

Wyer, R. S. and Carlston, D. E. (1979). *Social cognition, inference, and attribution*. Psychology Press.

Wyon, D. P., Wyon, I., and Norin, F. (1996). Effects of moderate heat stress on driver vigilance in a moving vehicle. *Ergonomics*, 39(1):61–75.

Xiong, J., Lian, Z., Zhou, X., You, J., and Lin, Y. (2015). Investigation of gender difference in human response to temperature step changes. *Physiology and Behavior*, 151(1):426–440.

Yu, W., Vaneckova, P., Mengersen, K., Pan, X., and Tong, S. (2010). Is the association between temperature and mortality modified by age, gender and socio-economic status? *Science of the Total Environment*, 408(17):3513–3518.

7 Tables

Table 1: Summary Statistics

	Mean	Std. Dev.
Grant indicator	0.164	0.371
Temperature (°F)	57.37	15.721
Heat index (°F)	57.77	16.423
Air pressure (pa)	29.688	0.759
Dew point (°F)	49.372	17.202
Precipitation (mm)	0.003	0.014
Wind speed (km/h)	4.557	3.441
Sky cover (percent)	55.44	0.276
Ozone (ppm)	0.0220	0.0120
CO (ppm)	0.917	0.496
$PM_{2.5}$ (μ/m^3)	14.957	11.569

Table 2: Fixed effect estimates: 6 AM - 4 PM average

	(1) Preferred	(2) 1-Day lag	(3) 1-Day lead	(4) All
$Temperature_t/1000$	-1.075***	-1.454***	-1.208***	-1.617***
	[0.274]	[0.406]	[0.382]	[0.486]
$Temperature_{t-1}/1000$	-	0.361	-	0.372
	-	[0.278]	-	[0.277]
$Temperature_{t+1}/1000$	-	-	0.139	0.159
	-	-	[0.260]	[0.260]
F-statistic of joint significance of weather variables	3.41	3.07	2.99	2.73
P-value	0.0026	0.0036	0.0044	0.0059
Observations	206,924	206,924	206,924	206,924

Notes: The unit of analysis is an immigration case. Dependent variable is a dummy taking value one if decision is favourable to applicant, zero otherwise. Temperature is the 6 AM to 4 PM average in the city in which the case is adjudicated, on the day of adjudication, in Fahrenheit. The temperature measure is divided by 1000 to reduce decimal places. All regressions control for weather, pollution and time fixed effects. Weather covariates include dew point, air pressure, wind speed, precipitation and cloud cover measured as 6 AM to 4 PM averages in the city in which the case is adjudicated, on the day of adjudication. Pollutant covariates include controls for ozone, carbon monoxide and PM_{25}, measured as calendar daily averages at the air quality monitoring station closest to the courthouse of adjudication, on the day of adjudication. Time fixed effects include day of week and year dummies relating to the day of adjudication. Regressions also include city-month fixed effects, name of judge adjudicating case, type of application and nationality of applicant. Sample is all cases adjudicated at 42 mainland US federal immigration courthouse locations from 1 January 2000 to 30 September 2004. Standard errors are clustered on city-month in brackets. * significant at 10% ** significant at 5% *** significant at 1%.

Table 3: Alternative fixed effects

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
$Temperature_t/1000$	-1.470***	-0.717***	-0.727***	-0.780***	-0.806***	-1.037***	-0.893***	-1.082***	-0.939***	-1.075***
	[0.355]	[0.270]	[0.273]	[0.269]	[0.249]	[0.278]	[0.215]	[0.271]	[0.285]	[0.274]
Hausman-test	1.40	0.76	0.69	0.44	0.63	0.40	0.36	0.90	0.09	-
P-value	0.236	0.384	0.406	0.506	0.426	0.528	0.549	0.343	0.760	-
Observations	206,924	206,924	206,924	206,924	206,924	206,924	206,924	206,924	206,924	206,924
Nationality FEs	N	Y	Y	Y	Y	Y	Y	Y	Y	Y
Day of week FEs	N	N	Y	Y	Y	Y	Y	Y	N	Y
Type of application FEs	N	N	N	Y	Y	Y	Y	Y	Y	Y
Judge FEs	N	N	N	N	Y	Y	Y	N	Y	Y
City-month FEs	N	N	N	N	N	Y	N	N	Y	Y
Judge-month FEs	N	N	N	N	N	N	N	Y	N	N
City FEs	N	N	N	N	N	N	Y	Y	N	N
Year FEs	N	N	N	N	N	N	N	Y	Y	Y
Year-month FEs	N	N	N	N	N	N	Y	N	N	N
Date FEs	N	N	N	N	N	N	N	N	Y	N

Notes: The unit of analysis is an immigration case. Dependent variable is a dummy taking value one if decision is favourable to applicant, zero otherwise. Temperature is the 6 AM to 4 PM average in the city in which the case is adjudicated, on the day of adjudication, in Fahrenheit. The temperature measure is divided by 1000 to reduce decimal places. All regressions control for weather and pollution. Weather covariates include dew point, air pressure, wind speed, precipitation and cloud cover measured as 6 AM to 4 PM averages in the city in which the case is adjudicated, on the day of adjudication. Pollutant covariates include controls for ozone, carbon monoxide and PM_{25}, measured as calendar daily averages at the air quality monitoring station closest to the courthouse of adjudication, on the day of adjudication. Each specification contains other controls as indicated. Column (10) coincides with column (1) from Table 2, our preferred specification. Sample is all cases adjudicated at 42 mainland US federal immigration courthouse locations from 1 January 2000 to 30 September 2004. Standard errors are clustered on city-month in brackets. * significant at 10% ** significant at 5% *** significant at 1%.

Table 4: Sensitivity analyses

	(1) Preferred spec.	(2) Calendar day	(3) Deviation from weekly avg.	(4) City × Temp interactions	(5) Winter exclusion	(6) Rain × temp interactions
$Temperature_t/1000$	-1.075***	-0.750***	-0.618**	-1.520***	-1.160***	-1.238***
	[0.274]	[0.256]	[0.309]	[0.466]	[0.330]	[0.298]
$Temperature_t/1000 \times Rain_t$	-	-	-	-	-	-0.336
	-	-	-	-	-	[0.274]
Observations	206,924	168,794	206,924	206,924	156,951	206,924
City*Temperature	N	N	N	Y	N	N
Temperature*Rain	N	N	N	N	N	Y

Notes: The unit of analysis is an immigration case. Dependent variable is a dummy taking value one if decision is favourable to applicant, zero otherwise. Temperature is the 6 AM to 4 PM average in the city in which the case is adjudicated, on the day of adjudication, in Fahrenheit. The temperature measure is divided by 1000 to reduce decimal places. All regressions control for weather, pollution and time fixed effects. Weather covariates include dew point, air pressure, wind speed, precipitation and cloud cover measured as 6 AM to 4 PM averages in the city in which the case is adjudicated, on the day of adjudication. Pollutant covariates include controls for ozone, carbon monoxide and PM_{25}, measured as calendar daily averages at the air quality monitoring station closest to the courthouse of adjudication, on the day of adjudication. Time fixed effects include day of week and year dummies relating to the day of adjudication. Regressions also include city-month fixed effects, name of judge adjudicating case, type of application and nationality of applicant. Sample is all cases adjudicated at 42 mainland US federal immigration courthouse locations from 1 January 2000 to 30 September 2004. Column (1) repeats column (1) from Table 2, the preferred specification. In column (2) we re-estimate the preferred specification but with the temperature variable defined as calendar day average in Fahrenheit, divided by 1000. In column (3) we re-estimate the preferred specification replacing the temperature measure with deviation of 6 AM to 4 PM average temperature in city of adjudication on date of adjudication from what is average for that city for that week of the year. In column (4) we re-estimate the preferred specification but adding city times temperature interactions. In column (5) we re-estimate the preferred specification excluding cases adjudicated on dates in December, January and February. In column (6) we re-estimate the preferred specification including rain times temperature interactions. Standard errors are clustered on city-month in brackets. * significant at 10% ** significant at 5% *** significant at 1%.

Table 5: Robustness

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	Preferred	Pollution exclusion	CA exclusion	Clear sky days	Zero precipitation	Zero precipitation including lag	HI	HI (>75)	Quartiles exclusion	Deciles exclusion
$Temperature_t/1000$	-1.075***	-0.910***	-1.159***	-2.738**	-1.304***	-1.281***	-	-	-0.707*	-1.064***
	[0.274]	[0.269]	[0.384]	[1.144]	[0.318]	[0.328]	-	-	[0.424]	[0.299]
$Heatindex_t/1000$	-	-	-	-	-	-	-0.437**	-1.991**	-	-
	-	-	-	-	-	-	[0.195]	[0.772]		-
Observations	206,924	206,924	135,184	13,981	133,890	111,361	206,921	29,659	102,408	163,890

Notes: The unit of analysis is an immigration case. Dependent variable is a dummy taking value one if decision is favourable to applicant, zero otherwise. Temperature is the 6 AM to 4 PM average in the city in which the case is adjudicated, on the day of adjudication, in Fahrenheit. The temperature measure is divided by 1000 to reduce decimal places. All regressions control for weather, pollution and time fixed effects. Weather covariates include dew point, air pressure, wind speed, precipitation and cloud cover measured as 6 AM to 4 PM averages in the city in which the case is adjudicated, on the day of adjudication. Pollutant covariates include controls for ozone, carbon monoxide and PM_{25}, measured as calendar daily averages at the air quality monitoring station closest to the courthouse of adjudication, on the day of adjudication. Time fixed effects include day of week and year dummies relating to the day of adjudication. Regressions also include city-month fixed effects, name of judge adjudicating case, type of application and nationality of applicant. Sample is all cases adjudicated at 42 mainland US federal immigration courthouse locations from 1 January 2000 to 30 September 2004. Column (1) repeats column (1) from Table 2, the preferred specification. Column (2) excludes pollution covariates. Column (3) excludes all cases adjudicated in California. Column (4) is estimated only on cases when 6 AM to 4 PM cloud cover was below 10% in city of adjudication on day of adjudication. Column (5) is estimated only on cases where there was no precipitation in city of adjudication on day of adjudication. Column (6) is estimated only on cases where there was no precipitation in city of adjudication on day of adjudication or the day before. Column (7) repeats the preferred specification but replacing the temperature variable with heat index. Column (8) re-estimates specification in column (7) but only on cases adjudicated on days when heat index exceeded 75 °F. Columns (9) and (10) re-estimate the preferred specification but excluding cases adjudicated by judges in the top and bottom quartile, or top and bottom decile, by overall leniency. Standard errors are clustered on city-month in brackets. * significant at 10% ** significant at 5% *** significant at 1%.

Table 6: Placebos

	(1) Preferred	(2) +100 days	(3) -100 days	(4) Furthest monitor
$Temperature_t/1000$	-1.075***	-0.000237	0.0000730	-0.00000945
	[0.274]	[0.000148]	[0.000157]	[0.000230]
Observations	206,924	206,924	206,924	206,924

Notes: All specifications coincide with column (1) in Table 2, our preferred specification. Column (2) re-estimates the preferred specification but replacing the temperature variable with the temperature in the city of adjudication 100 days after the case is adjudicated. Column (3) re-estimates the preferred specification but replacing the temperature variable with the temperature in the city of adjudication 100 days before the case is adjudicated. Column (4) re-estimates the preferred specification but replacing the temperature variable with the temperature on the date of adjudication at the courthouse location in mainland US furthest from the courthouse of adjudication. * significant at 10% ** significant at 5% *** significant at 1%.

Table 7: Parole: Calendar day

	(1) Preferred	(2) 1-Day lag	(3) 1-Day lead	(4) All
$Temperature_t/1000$	-1.560***	-2.188***	-1.586**	-2.378**
	[0.468]	[0.779]	[0.746]	[1.116]
$Temperature_{t-1}/1000$	-	0.763	-	0.802
	-	[0.720]	-	[0.752]
$Temperature_{t+1}/1000$	-	-	0.0319	0.194
	-	-	[0.762]	[0.793]
Observations	18,461	18,461	18,461	18,461

Notes: The unit of analysis is a parole case. Dependent variable is a dummy taking value one if decision is favourable to applicant, zero otherwise. Temperature is daily average at the monitoring station closest to the decision venue, in Fahrenheit. The temperature measure is divided by 1000 to reduce decimal places. All regressions control for weather, pollution and time fixed effects. Weather covariates include dew point, air pressure, wind speed, precipitation and cloud cover daily averages. Pollutant covariates include controls for ozone, carbon monoxide and nitrogen dioxide, measured as daily averages at the air quality monitoring station closest to the venue of decision on the date of decision. Time fixed effects include day of week and year dummies relating to the day of decision. Regressions also include venue-month fixed effects, commissioners' name, type of application and name of inmate. Sample consists of data on all parole hearings conducted by the Board of Parole Hearing (BPH) between 3 January 2012 and 18 December 2015 is from the California Department of Corrections and Rehabilitation (CDCR). Standard errors are clustered on venue-month in brackets. * significant at 10% ** significant at 5% *** significant at 1%.

Figures

Figure 1: Location of immigration courts (excluding Honolulu)

Figure 2: US immigration courts

Notes: Buildings that house the 16 largest courts ranked by contribution to sample. From left-to-right, top row: New York, Los Angeles, Miami, San Francisco, Chicago, Arlington, Orlando, Baltimore, Boston, Detroit, Philadelphia, Memphis, Atlanta, Houston, San Diego, Seattle.

Figure 3: Location of parole hearing venues

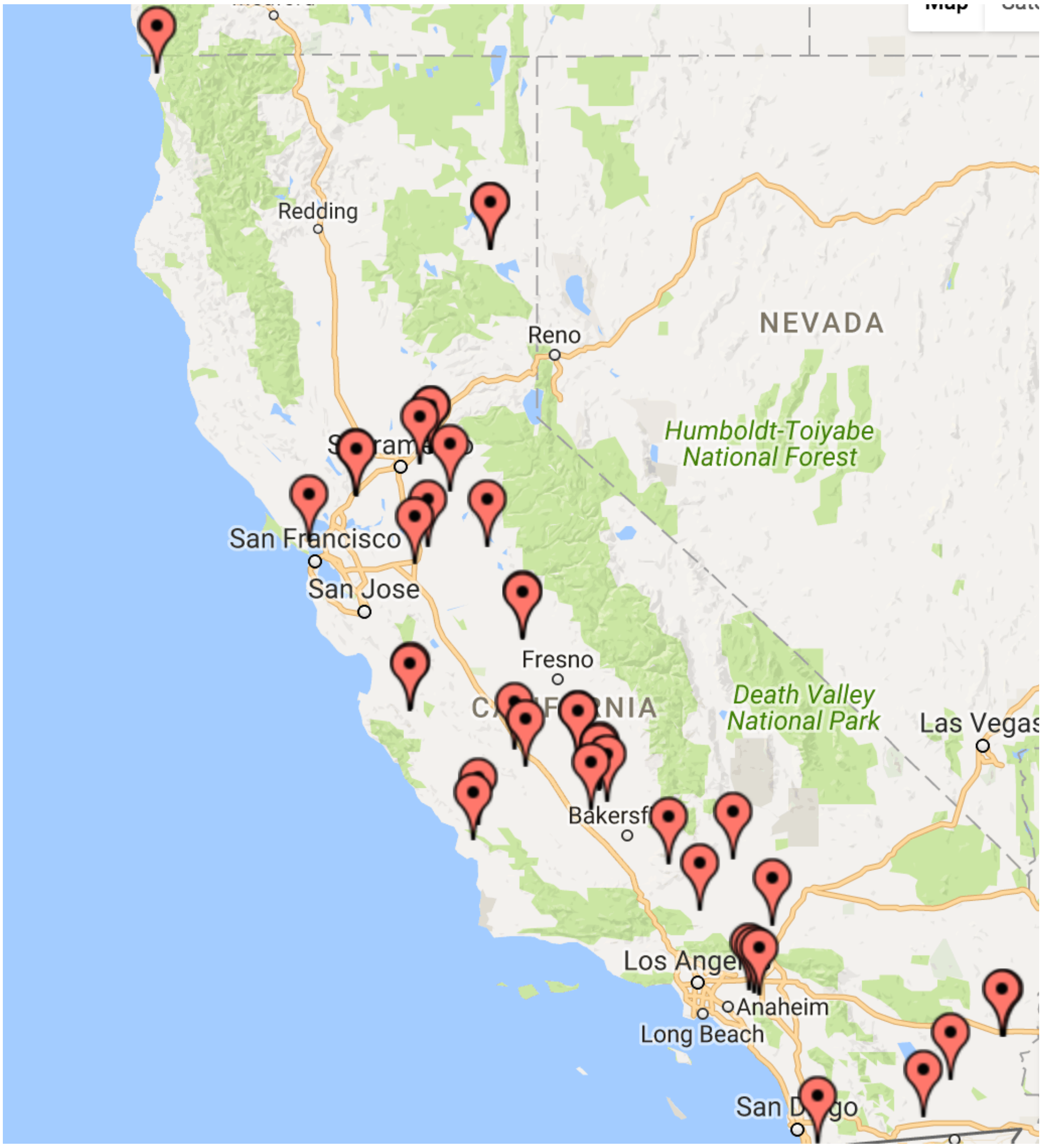
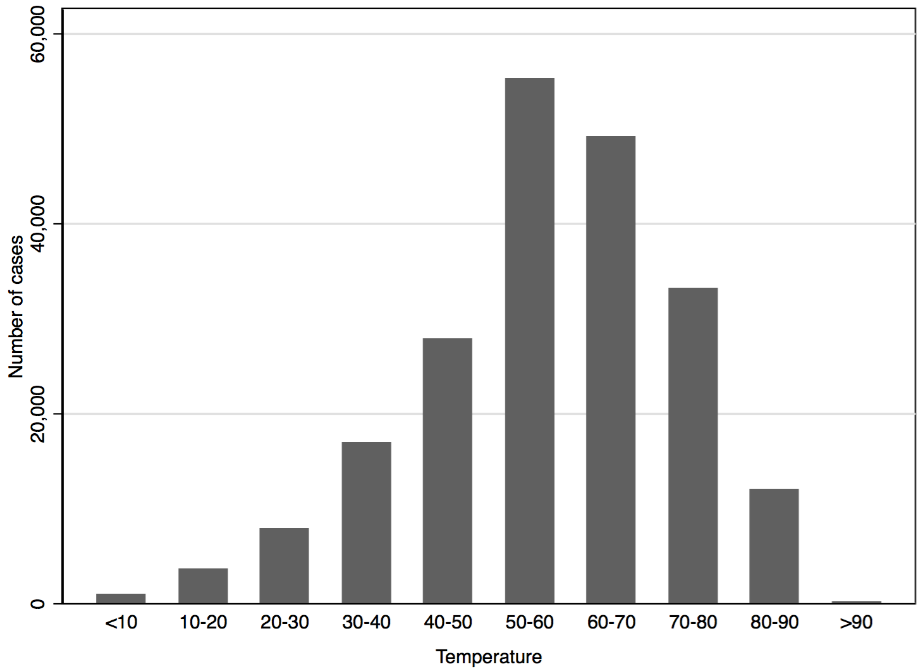
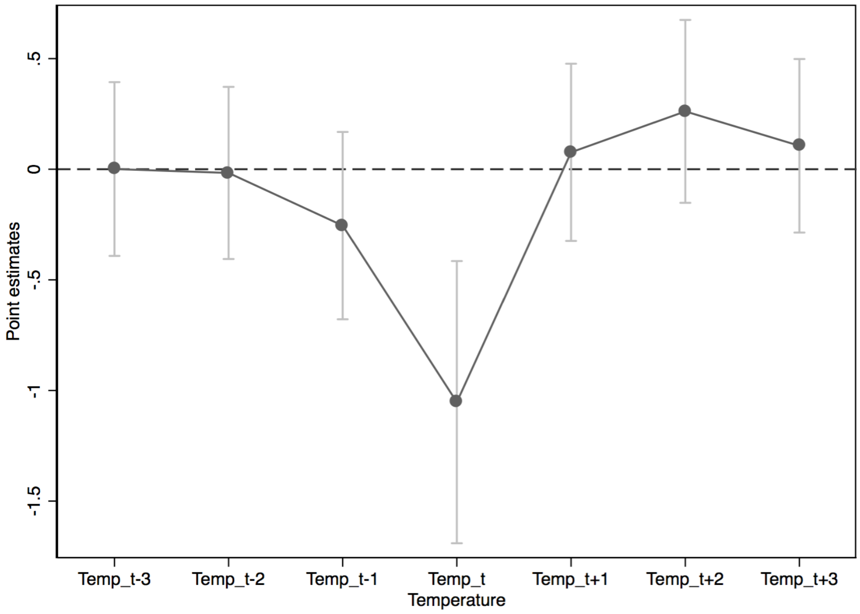


Figure 4: Distribution of cases over 6 AM - 4 PM temperature bins



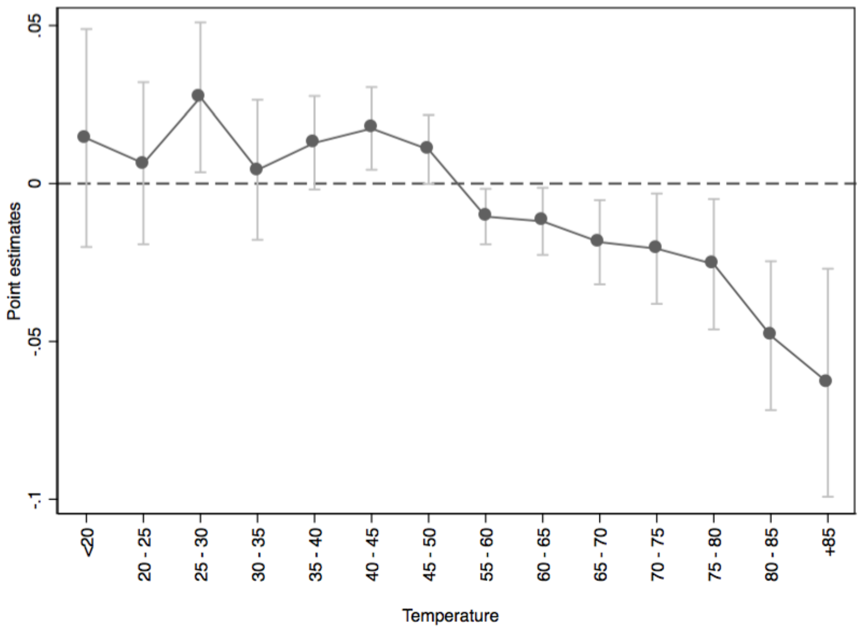
Notes: This figure plots number of cases adjudicated over 6 AM to 4 PM temperature bins at 42 mainland US federal immigration courthouse locations from 1 January 2000 to 30 September 2004.

Figure 5: Timing of exposure: 6 AM - 4 PM



Notes: This figure plots the coefficients that result from running the specification in column (1) of Table (2) but including three lags and three leads of the temperature variable. Grey lines show the 95 percent confidence intervals based on standard errors clustered on city-month.

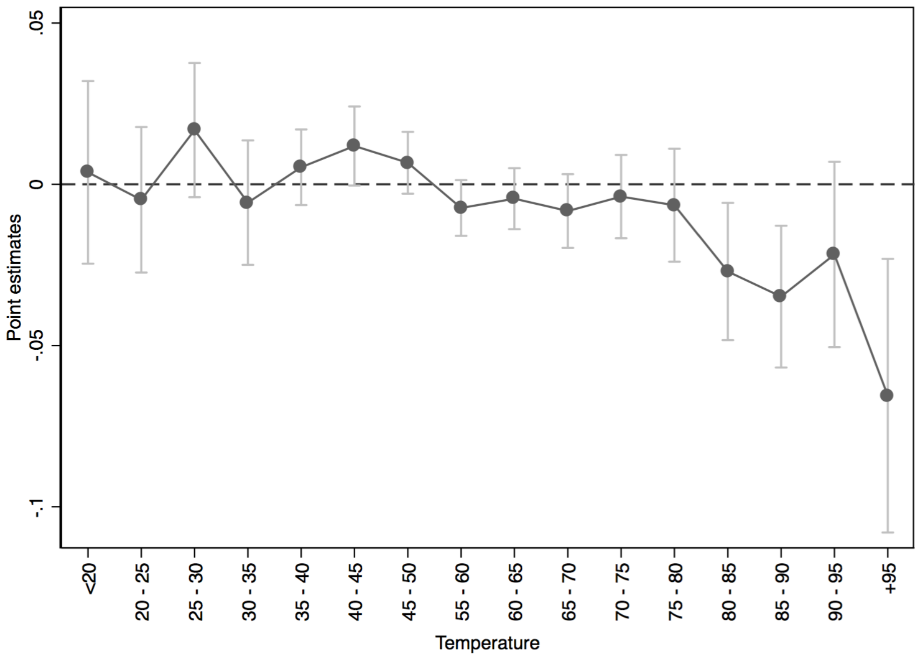
Figure 6: Non-linear estimates: Temperature, 6 AM - 4 PM



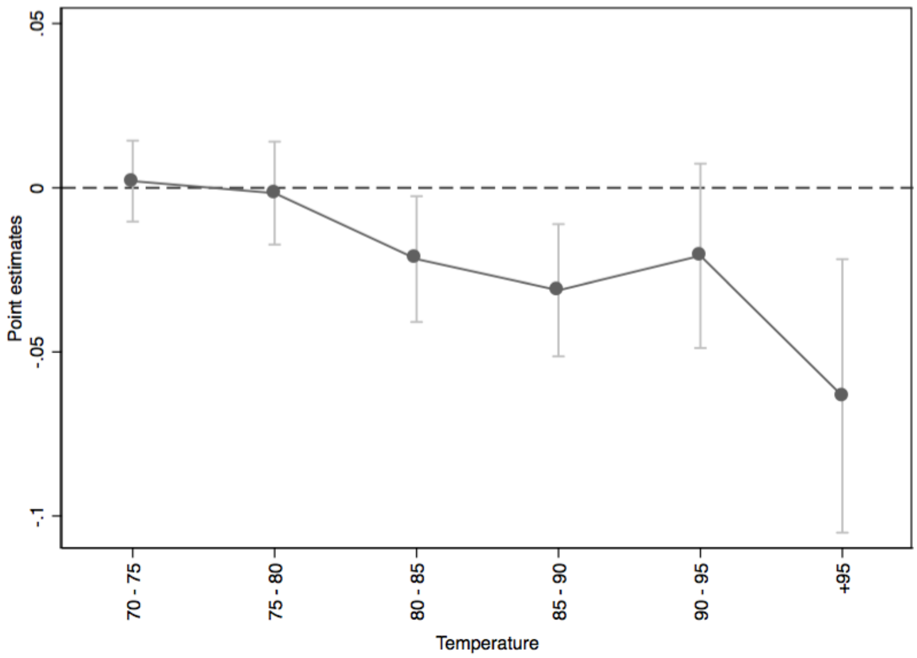
Notes: This figure plots the coefficients on the temperature indicator variables from estimation of the non-linear specification reported in column (1) from Table A.3. Grey lines show the 95 percent confidence intervals based on standard errors clustered on city-month.

Figure 7: Non-linear estimates: Heat index, 6 AM - 4 PM

(a) Whole sample

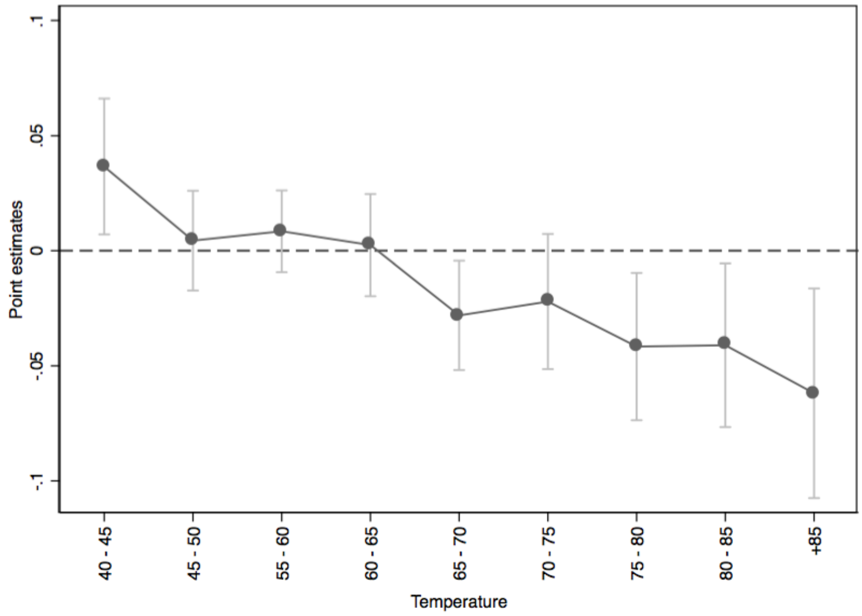


(b) HI > 65



Notes: This figure plots the coefficients on the heat index indicator variables from estimation of the non-linear specifications reported in columns (2) and (3) from Table A.3. Grey lines show the 95 percent confidence intervals based on standard errors clustered on city-month.

Figure 8: Non-linear estimates: Parole, temperature, calendar day



Notes: This figure plots the coefficients on the temperature indicator variables from estimation of a non-linear variant of the specification reported on column (1) from Table 7. The non-linear variant replaces the continuous temperature measure with a series of temperature indicator variables of width 5 degrees Fahrenheit. Grey lines show the 95 percent confidence intervals based on standard errors clustered on venue-month.

A Appendix

Table A.1: Extended fixed effect estimates: 6 AM - 4 PM average

	(1) Preferred	(2) 1-Day lag	(3) 1-Day lead	(4) All
$Temperature_t/1000$	-1.075***	-1.454***	-1.208***	-1.617***
	[0.274]	[0.406]	[0.382]	[0.486]
$Temperature_{t-1}/1000$	-	0.361	-	0.372
	-	[0.278]	-	[0.277]
$Temperature_{t+1}/1000$	-	-	0.139	0.159
	-	-	[0.260]	[0.260]
$Airpressure_t$	-0.00494	-0.00500	-0.00515	-0.00523
	[0.00518]	[0.00518]	[0.00516]	[0.00516]
$Dewpoint_t$	0.000723***	0.000765***	0.000780***	0.000777***
	[0.000213]	[0.000217]	[0.000217]	[0.000222]
$Precipitation_t$	0.0616	0.0590	0.0625	0.0600
	[0.0822]	[0.0821]	[0.0820]	[0.0818]
$Windspeed_t$	0.000738	0.000771	0.000820	0.000866
	[0.000490]	[0.000485]	[0.000548]	[0.000543]
$Skycover_t$	-0.00292	-0.00159	-0.00186	-0.000343
	[0.00501]	[0.00515]	[0.00538]	[0.00551]
$Ozone_t$	0.493***	0.503***	0.485***	0.494***
	[0.160]	[0.160]	[0.157]	[0.157]
CO_t	0.00572	0.00547	0.00552	0.00523
	[0.00389]	[0.00389]	[0.00385]	[0.00384]
PM_{25t}	-0.00000866	-0.0000104	-0.0000130	-0.0000153
	[0.0000987]	[0.0000986]	[0.000100]	[0.0000999]
F-statistic	3.41	3.07	2.99	2.73
P-value	0.0026	0.0036	0.0044	0.0059
Observations	206,924	206,924	206,924	206,924

Notes: The unit of analysis is an immigration case. Dependent variable is a dummy taking value one if decision is favourable to applicant, zero otherwise. Temperature is the 6 AM to 4 PM average in the city in which the case is adjudicated, on the day of adjudication, in Fahrenheit. The temperature measure is divided by 1000 to reduce decimal places. All regressions control for weather, pollution and time fixed effects. Weather covariates include dew point, air pressure, wind speed, precipitation and cloud cover measured as 6 AM to 4 PM averages in the city in which the case is adjudicated, on the day of adjudication. Pollutant covariates include controls for ozone, carbon monoxide and PM_{25}, measured as calendar daily averages at the air quality monitoring station closest to the courthouse of adjudication, on the day of adjudication. Time fixed effects include day of week and year dummies relating to the day of adjudication. Regressions also include city-month fixed effects, name of judge adjudicating case, type of application and nationality of applicant. Sample is all cases adjudicated at all 42 mainland US federal immigration courthouse locations from 1 January 2000 to 30 September 2004. Standard errors are clustered on city-month in brackets. * significant at 10% ** significant at 5% *** significant at 1%.

Table A.2: Heterogeneity by gender of judge

	(1) Whole sample	(2) Female	(3) Male
$Temperature_t/1000$	-1.075***	-1.128**	-1.064***
	[0.274]	[0.494]	[0.330]
Observations	206,924	72,229	134,695
Hausman test	3.65**		
P-value	0.0325		

Notes: Column (1) re-states column (1) of Table 2, the preferred specification. Column (2) re-estimates this specification only on cases adjudicated by a female judge. Column (3) re-estimates this specification only on cases adjudicated by a male judge.

Table A.3: Non-linear estimates

	(1) Temperature	(2) Heat Index	(3) HI>65
X ≤20	0.0144	0.00428	-
	[0.0176]	[0.0162]	-
X ∈ [20-25)	0.00642	-0.00409	-
	[0.0131]	[0.0118]	
X ∈ [25-30)	0.0273**	0.0167	-
	[0.0121]	[0.0108]	-
X ∈ [30-35)	0.00434	-0.00507	-
	[0.0113]	[0.00981]	-
X ∈ [35-40)	0.0129*	0.00590	-
	[0.00752]	[0.00595]	-
X ∈ [40-45)	0.0174***	0.0116*	-
	[0.00665]	[0.00639]	
X ∈ [45-50)	0.0108*	0.00659	-
	[0.00555]	[0.00496]	-
X ∈ [50-55)	-	-	-
	-	-	-
X ∈ [55-60)	-0.0105**	-0.00776*	-
	[0.00448]	[0.00420]	-
X ∈ [60-65)	-0.0120**	-0.00613	-
	[0.00541]	[0.00463]	-
X ∈ [65-70)	-0.0186**	-0.00926	-
	[0.00678]	[0.00562]	-
X ∈ [70-75)	-0.0206**	-0.00632	0.00204
	[0.00889]	[0.00657]	[0.00628]
X ∈ [75-80)	-0.0255**	-0.00932	-0.00162
	[0.0105]	[0.00942]	[0.00799]
X ∈ [80-85)	-0.0482***	-0.0285***	-0.0217**
	[0.0120]	[0.0107]	[0.00974]
X ∈ [85-90)	-0.0631***	-0.0369***	-0.0312***
	[0.0184]	[0.0113]	[0.0102]
X ∈[90-95)	-	-0.0259*	-0.0207
	-	[0.0146]	[0.0143]
X ≥ 95	-	-0.0701***	-0.0634***
	-	[0.0202]	[0.0206]
Observations	206,924	206,924	67,194

Notes: The unit of analysis is an immigration case. Dependent variable is a dummy taking value one if decision is favourable to applicant, zero otherwise. Temperature bins are indicators for every 5 °F of 6 AM to 4 PM temperature in the city of which the case is adjudicated, on the day of adjudication, with the 50 - 55 °F bin as the reference category. All regressions control for weather, pollution and time fixed effects. Weather covariates include dew point, air pressure, wind speed, precipitation and cloud cover measured as 6 AM to 4 PM averages in the city in which the case is adjudicated, on the day of adjudication. Pollutant covariates include controls for ozone, carbon monoxide and PM_{25}, measured as calendar daily averages at the air quality monitoring station closest to the courthouse of adjudication, on the day of adjudication. Time fixed effects include day of week and year dummies relating to the day of adjudication. Regressions also include city-month fixed effects, name of judge adjudicating case, type of application and nationality of applicant. Sample is all cases adjudicated at 42 mainland US federal immigration courthouse locations from 1 January 2000 to 30 September 2004. Column (2) repeats the specification in column (1) replacing the temperature variable with heat index. Column (3) re-estimates specification in column (2) but only on cases adjudicated on days when heat index exceeded 65 °F. Standard errors are clustered on city-month in brackets. * significant at 10% ** significant at 5% *** significant at 1%.

Table A.4: Alternative standard errors

	(1) City-week	(2) Year-month	(3) City-year	(4) City	(5) Judge	(6) Judge-month	(7) City and week	(8) Eicker-White	(9) Newey-West
$Temperature_t/1000$	-1.075***	-1.075***	-1.075***	-1.075***	-1.075***	-1.075***	-1.075***	-1.075***	-1.075***
	[0.297]	[0.242]	[0.313]	[0.306]	[0.271]	[0.273]	[0.320]	[0.197]	[0.196]
Observations	206,924	206,924	206,924	206,924	206,924	206,924	206,924	206,924	206,924

Notes: The unit of analysis is an immigration case. Dependent variable is a dummy taking value one if decision is favourable to applicant, zero otherwise. Temperature is the 6 AM to 4 PM average in the city in which the case is adjudicated, on the day of adjudication, in Fahrenheit. The temperature measure is divided by 1000 to reduce decimal places. All regressions control for weather, pollution and time fixed effects. Weather covariates include dew point, air pressure, wind speed, precipitation and cloud cover measured as 6 AM to 4 PM averages in the city in which the case is adjudicated, on the day of adjudication. Pollutant covariates include controls for ozone, carbon monoxide and PM_{25}, measured as calendar daily averages at the air quality monitoring station closest to the courthouse of adjudication, on the day of adjudication. Time fixed effects include day of week and year dummies relating to the day of adjudication. Regressions also include city-month fixed effects, name of judge adjudicating case, type of application and nationality of applicant. Sample is all cases adjudicated at 42 mainland US federal immigration courthouse locations from 1 January 2000 to 30 September 2004. Standard errors in brackets are clustered on city-week in column (1), year-month in column (2), city-year in column (3), city in column (4), judge in column (5), judge-month in column (5), city and week in column (6). Eicker-White and Newey-West standard errors reported in columns (7) and (8) in brackets. * significant at 10% ** significant at 5% *** significant at 1%.

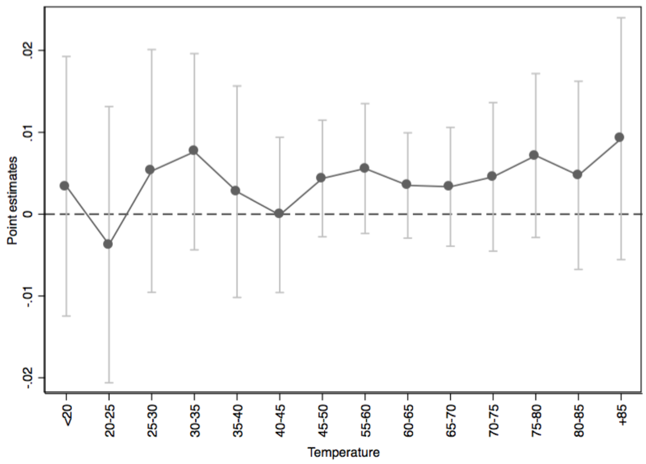
Table A.5: Randomization test

	Immigration				Parole		
	(1) Type of app.	(2) Middle East applicant	(3) Female judge	(4) Number of cases	(5) Type of app.	(6) Female judge	(7) Number of cases
$Temperature_t/1000$	0.241	0.131	-0.0216	0.747	0.901	-0.505	5.284**
	[0.233]	[0.136]	[0.358]	[1.350]	[0.681]	[1.584]	[1.688]
Judge FE	Y	Y	N	Y	Y	N	Y
Nationality FE	Y	N	Y	N	N	N	N
Type of application FE	N	Y	Y	N	N	Y	N
Observations	168,794	168,794	168,794	74,929	18,461	18,461	9,472

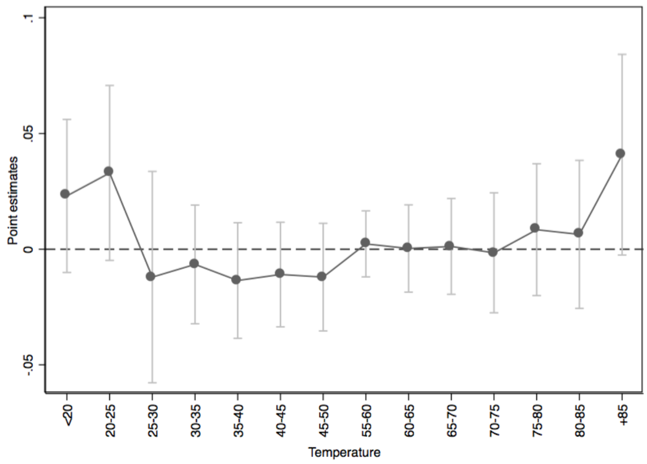
Notes: The unit of analysis is an immigration case. Dependent variable in columns (1) and (5) is a dummy for type of application, in column (2) is a dummy taking value one if an applicant is Middle Eastern origin, zero otherwise, in columns (3) and (6) is a dummy that takes value one if case is adjudicated by a female judge, zero otherwise and in columns (4) and (7) is total number of cases heard by each judge in each day. Temperature is the 6 AM to 4 PM average in the city in which the case is adjudicated, on the day of adjudication, in Fahrenheit. The temperature measure is divided by 1000 to reduce decimal places. All regressions control for weather, pollution and time fixed effects. Weather covariates include dew point, air pressure, wind speed, precipitation and cloud cover measured as 6 AM to 4 PM averages in the city in which the case is adjudicated, on the day of adjudication. Pollutant covariates include controls for ozone, carbon monoxide and PM_{25}, measured as calendar daily averages at the air quality monitoring station closest to the courthouse of adjudication, on the day of adjudication. Time fixed effects include day of week and year dummies relating to the day of adjudication. Regressions also include city-month fixed effects. Each specification contains other controls as indicated. Sample is all cases adjudicated at 42 mainland US federal immigration courthouse locations from 1 January 2000 to 30 September 2004. Standard errors are clustered on city-month in brackets. * significant at 10% ** significant at 5% *** significant at 1%.

Figure A.1: Non-linear randomization test: Asylum application

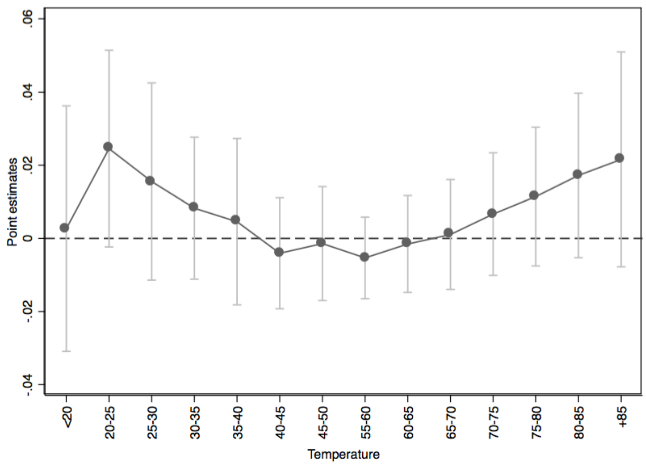
(a) Middle East



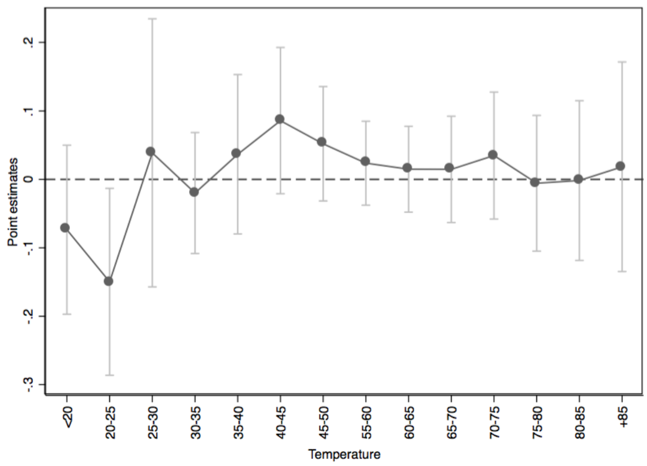
(b) Female judge



(c) Type of application



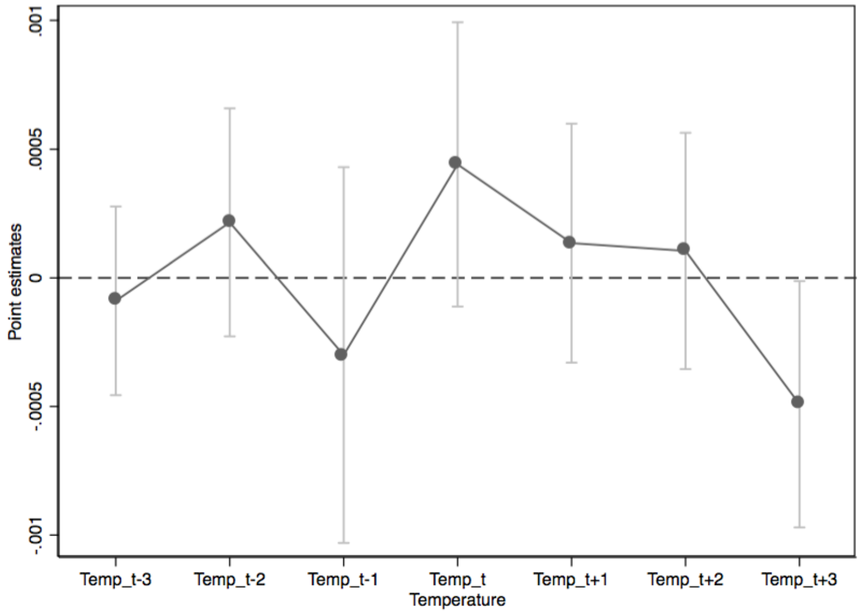
(d) Total cases



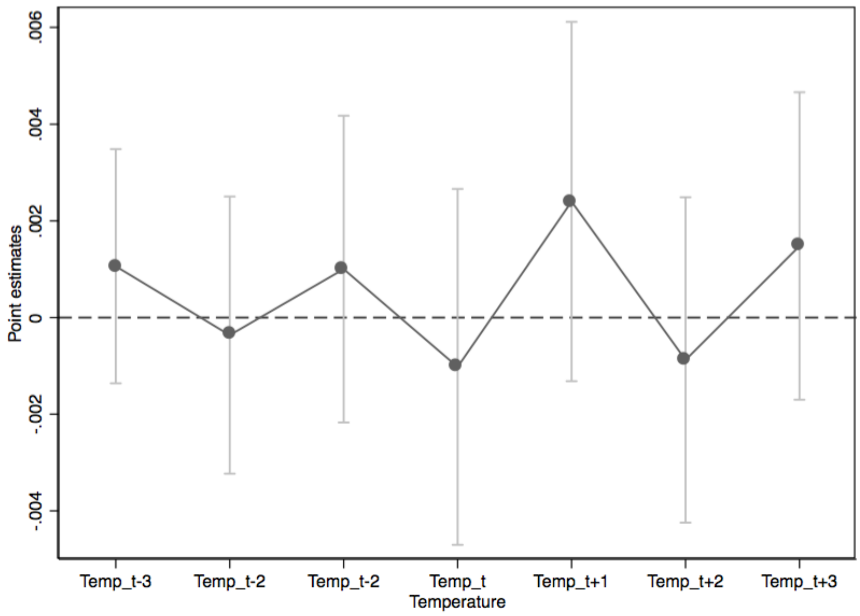
Notes: These figures plot the coefficients for the temperature indicator variables from estimation of the non-linear specification reported in column (1) of Table A.3 using different dependent variables. The dependent variable is in panel (a) a dummy taking value one if an applicant is Middle Eastern origin, zero otherwise in panel (b) a dummy taking value one if a judge is female, in panel (c) a dummy for type of application and in panel (d) the total number of cases heard by a judge on a day. Grey lines show the 95 percent confidence interval based on standard errors clustered on city-month.

Figure A.2: Timing of exposure

(a) Type of application



(b) Total number of cases



Notes: These figures plot the coefficients that result from running the specification in columns (1) and (4) of Table A.5 but including three lags and three leads of the temperature variable. Grey lines show the 95 percent confidence intervals based on standard errors clustered on city-month.